Ecological Monitoring

On Army Lands

LAND CONDITION TREND ANALYSIS II

LCTA II
Technical Reference Manual

Chapter 11
Data Analysis and Interpretation

June 1999

11 Data Analysis and Interpretation

This instructional document is intended as a generic guide to help ITAM personnel and others address issues related to data analysis and interpretation in the context of the Integrated Training Area Management (ITAM) Program and DoD land management. For this reason, it does not specifically address Land Condition-Trend Analysis (LCTA) program goals and objectives, which may change over time. Examples of data analyses are taken from a variety of sources ranging from traditional to innovative and simple to complex in nature. Methods presented here are equally appropriate for examining training-related and conservation-related issues or problems, and examples draw from both types.

11.1 Introduction

Data analysis and interpretation should be related directly to management and monitoring objectives as outlined in implementation plans and monitoring protocols. A discussion and examples of management and monitoring objectives are presented in Chapter 2. Just as management and monitoring goals and objectives determined the selection of data collection methods and sampling designs, they can also be used to formulate specific questions which direct data analysis approaches and procedures. For example, are you interested in comparing mean values with a threshold value, detecting changes over time, or examining cause-and-effect or correlative relationships? Monitoring objectives that are very specific may explicitly state what type of statistical comparison will be used and at what level of confidence. In some cases a number of different analyses can use the same data to explore relationships and differences, both temporal and spatial. Monitoring may document changes and/or relationships that were unforeseen at the outset of implementation, thus necessitating a re-evaluation of approaches and methodologies.

Data analysis and interpretation should be documented and performed in as straightforward a manner as possible, allowing for replication of procedures and comparisons of future analyses with results from previous years. Presentation (i.e., reporting of results) should be done at a level that is appropriate to the audience or reader. Examples of different audiences include the military training community (e.g., Training Directorate, Range Control), natural resources staff, the public, or scientific/professional forums. The framework of a monitoring or LCTA report is discussed in Section 5.

11.2 Analyzing Monitoring Data

11.2.1 Overview of Statistical Applications

The choice and application of analysis tools is largely determined by the level of monitoring that is being used and the type of data that is collected, which in turn is related to the monitoring objectives that have been specified. Descriptions and applicability of different levels of monitoring are presented in section 2.1.4 (Levels of Monitoring). Quantitative approaches to data analysis consist of descriptive and inferential statistics. Descriptive statistics consists of methods for organizing and summarizing information in a clear and effective way (e.g., means and measures of variability). Inferential statistics consists of methods of drawing conclusions about a population or relationships based on information obtained from a sample of the population. Inferential statistics can be used to analyze population differences, make associations between two or more factors that have been measured, examine the effect on one factor from changes to other factors, and examine whether a management action is having the desired effect. Statistics allow the user to make inferences about the population from a sample because it provides a measure of precision or variation with regard to the sample data. Sample estimates without measures of variation have limited use because it is not possible to know the proximity of the sample mean to the “true” value.

Monitoring objectives generally focus on parameter estimation and change detection over time. The primary inferential procedures for addressing these issues are confidence intervals and statistical tests. Confidence intervals can be used for both point estimates (e.g., estimates for a single point in time) and estimating changes over time. Statistical tests are a way to determine the probability that a result occurs by chance alone.

11.2.2 Types of Data

The primary types of data that will be considered in this section are abundance data and frequency data. Although the approaches to interpreting these types of data are similar (parameter estimation and testing for differences), the methods of statistical analyses are different. Abundance data includes density and cover information. This data is considered interval or continuous data, where quantities are counted or estimated on a continuous scale (i.e., height, density, cover, length). Data on the number of individuals or items falling into various categories is considered frequency data (e.g., in how many of 50 frames surveyed did species A occur?). Frequency is based on presence or absence, and is not a true measure of abundance. For example, if a particular species or condition is present, there is no way to compare different levels of abundance (or degree) among different quadrats. Frequency data can be analyzed according to the normal distribution or the binomial distribution, depending on the sampling design and distribution of the data.

11.3 Confidence Intervals

A confidence-interval estimate for the population mean, based on sample data, provides information about the accuracy of the estimate. The confidence level of a confidence interval for a population mean signifies the confidence of the estimate. That is to say, it expresses the confidence we have that the estimated value actually lies within the confidence interval. The width of the confidence interval indicates the precision of the estimate; wide confidence intervals indicate poor precision (or high variability), while narrow confidence intervals indicate good precision. For a fixed sample size, the greater the required level of confidence, the greater the width of the confidence interval. Commonly-used levels of confidence are 80%, 90%, 95%, and 99%. For natural resources management purposes, confidence levels of more than 95% are generally impractical, expensive, and unnecessary. The confidence level chosen should be reflective of the amount of risk you are willing to accept in making a false conclusion based on a confidence interval (i.e., the confidence interval does not in fact contain the true population mean).

11.3.1 Assumptions

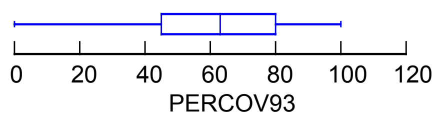
Confident intervals are a form of parametric statistics (data are assumed to have an approximate normal distribution) that rely on several assumptions in order to interpret results with the appropriate level of confidence. If the assumptions are violated, the validity of the confidence intervals may be suspect. Several visual approaches for testing assumptions for parametric statistics are presented in Figure 123.

The basic assumptions and guidelines for using confidence intervals are:

a) The data (samples) have a normal distribution. In statistics, the Central Limit Theorem (CLT) states that the sampling distribution of means will be approximately normally distributed for large samples even if the population is not normally distributed. Thus confidence intervals can often be used despite non-normal parent distributions, as long as the departure from normality is not too severe and the sample size is large enough. In community and population-level monitoring, the CLT is usually applicable where $n \geq 10$ (The Nature Conservancy 1997).
b) Samples are independent. It is important that the samples are not related or correlated. Random sampling helps to ensure that samples are independent. This assumption is violated by samples from permanent plots, where the value of a measurement will often be related to the value of subsequent measurements.
c) Samples are random and unbiased. Restricting data collection to representative, typical, or "key" areas does not constitute a random sample (Green 1979).
d) Variances are equal. This assumption applies only to comparisons of two or more samples. Samples are typically assumed to have similar variances. Large differences in sample sizes can contribute to unequal variances.

When one or more of these assumptions about the population is seriously violated, then nonparametric statistics are used.

A.



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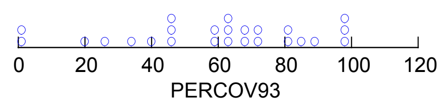

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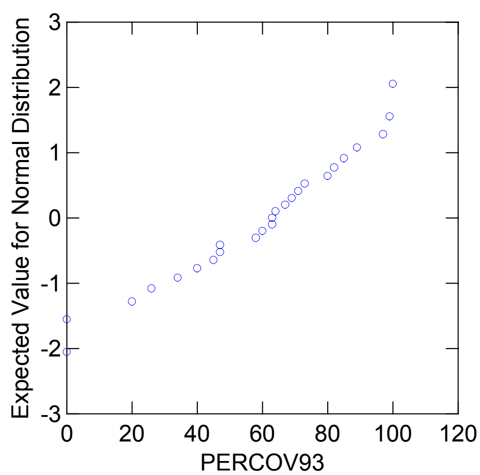


Figure 123. Graphical approaches to examining data distribution. A. Box plot, B. Dot histogram (dit) plot, C. Normal probability plot.

11.3.2 Calculating Confidence Intervals

The confidence interval for the estimated population mean is calculated using the following equation:

$$\overline{X} \pm t_{\alpha,v} s_{\overline{X}}$$

where:
t = the critical t value for a confidence level of 1-α and n-1 degrees of freedom
v = number of degrees of freedom = n-1
$S_{\bar{x}}$ = standard deviation of the estimated mean or standard error of the mean (SE or SEM))

where $S_{\bar{x}} = \frac{\text{standard deviation}}{\sqrt{n}}$

A two-tailed t table is used (see Appendices). In words, we can say that we are 1-α confidence that the confidence interval contains the true mean. When referring to a confidence interval, the quantity 1-α (e.g., 1-0.1 = 0.90 or 90%) is referred to as the confidence level. Note that as the standard deviation of the mean becomes smaller, the confidence interval also becomes smaller. Also, as sample size n increases, standard deviation of the mean typically gets smaller. As the confidence level increases (i.e., as α gets smaller), the confidence interval becomes larger. A large α produces a more narrow confidence interval.

11.3.3 Comparing a Point Estimate to a Threshold Value

Often, it is desirable to know if a resource has achieved a particular status or condition, sometimes referred to as a management threshold. By specifying management thresholds expressed as numerical goals, land managers have a benchmark against which progress or lack of progress can be measured. For example, a management objective may specify a minimum population size for a particular species of concern. Constructing a confidence interval for a point estimate is the most straightforward application of confidence intervals. If the threshold value is included in the confidence interval (i.e., the confidence interval overlaps with the threshold value), there is no statistical difference at the specified confidence level (e.g., 90%).

11.3.3.1 Example 1: Cover/Abundance (normal distribution)

Canopy cover of perennial grasses was measured on grassland plots on a parcel of land in Georgia (Figure 124). Sampling was conducted in 1991 and 1993 on 25 vegetation transects. The management objective was to maintain at least 70% perennial plant cover. The monitoring objective was to determine whether perennial plant cover was at least 70%. The following steps are necessary: (1) calculate the mean ($\bar{x}$), standard deviation (s), and standard error of the mean (SE) for each sample; (2) calculate the confidence interval as $\bar{x} \pm (t_{\alpha,v} \times SE)$. Sample data is presented in Table 33.

Table 33. Sample data for calculating confidence intervals.

	Sample ID	Percent Perennial Cover 1991	1993
	10	57	63
	16	72	99
	21	84	47
	22	70	58
	24	37	67
	44	46	60
	60	80	100
	61	2	0
	62	2	0
	66	43	69
	67	30	34
	73	32	64
	90	79	82
	101	63	89
	103	66	40
	104	45	47
	106	47	63
	121	7	20
	124	69	97
	125	48	73
	136	79	85
	158	53	45
	161	33	26
	187	76	80
	188	30	71
mean		50	59.16
standard deviation		24.39	28.04
standard error		4.88	5.61

A table of values of the Student's t distribution is presented in section 11.15 (Appendix – Statistical Reference Tables).

The 90% confidence interval for 1991 mean perennial vegetation cover is:

$$
\begin{aligned}
&50 \pm (1.71)(4.88)\\
&= 50 \pm 8.34\\
&= 41.66 \text{ to } 58.34
\end{aligned}
$$

The 90% confidence interval for 1993 mean perennial vegetation cover is:

$$
\begin{aligned}
&59.16 \pm (1.71)(5.61)\\
&= 59.16 \pm 9.59\\
&= 49.57 \text{ to } 68.75
\end{aligned}
$$

Figure 124 illustrates that for both 1991 and 1993, perennial plant cover was less than 70% on grassland plots, with a 90% level of confidence. Based on these results, the management objective has not been achieved.

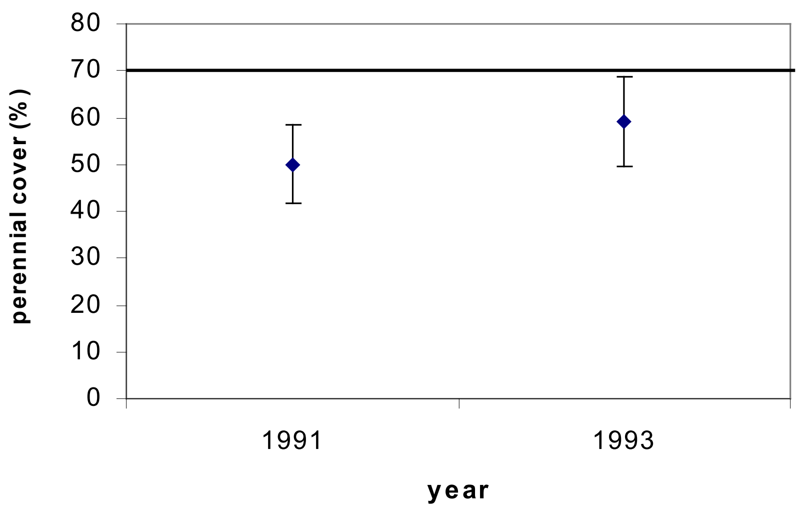


Figure 124. Percent perennial grass cover - means and 90% confidence intervals.

11.3.3.2 Example 2: Frequency or Proportional Data (binomial distribution)

The following example uses data from a Great Basin installation to examine the frequency of *Centaurea diffusa* (diffuse knapweed) within a particular watershed over a five year period. Data was collected on 100m –long transects, placing the frequency frame (in this case 60 cm X 60 cm) at 50 locations on either side of the transect for a total of 100 frames per sample. All frames were aggregated within a watershed where diffuse knapweed was considered a land management concern. Data is presented in Table 34.

Table 34. Frequency and confidence limits for diffuse knapweed over a five-year period.

year	# frames with diffuse knapweed present	# plots surveyed (100 frames/ plot)	total # of frequency quadrats surveyed	proportion of frames with diffuse knapweed	95% lower limit	95% upper limit
1991	830	22	2200	0.38	0.34	0.42
1992	798	30	3000	0.27	0.24	0.3
1993	1378	38	3800	0.36	0.32	0.40
1994	879	35	3500	0.25	0.21	0.28
1996	1488	34	3400	0.44	0.40	0.48

The results are presented graphically in Figure 125. If the monitoring objective is to detect whether knapweed frequency exceeds 0.4 (or 40% of samples), then the threshold is exceeded in 1991, almost exceeded in 1993, and exceeded again in 1996.

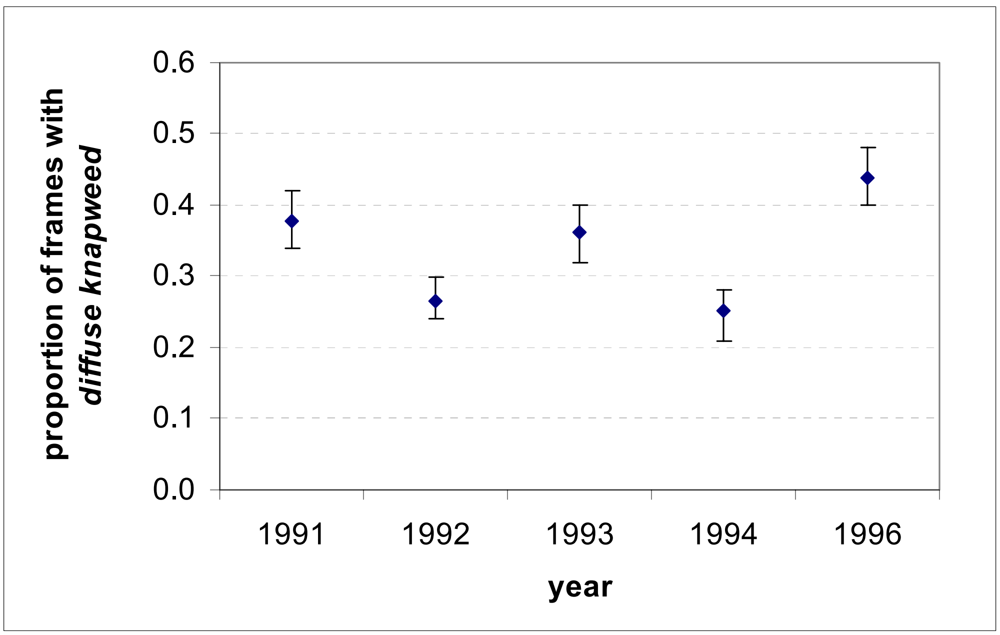


Figure 125. Frequency and confidence limits (95% level) for diffuse knapweed over a five-year period.

In this case, a 95% confidence level was chosen. Binomial confidence limits were taken from published tables (Rohlf and Sokal 1981) (see section 11.15 Appendix Statistical Reference Tables).

11.3.4 Comparing Two Independent Samples

This approach illustrates how confidence intervals are used to evaluate changes over time or differences between samples at the same point in time. For example, is the sample in year 1 different from the sample in year 2? There are two methods to address this type of question. The first uses confidence intervals for each point estimate (i.e., each time period). If the confidence intervals overlap greatly, the samples are not different, especially if the confidence interval of one sample includes the mean value of the other. If the confidence intervals do not overlap at all or are widely spaced, the samples are probably different. This method is an extension of the approach for point-estimate confidence intervals, discussed in section 11.3.3.

A second, more effective method, is to estimate the amount of change by developing a confidence interval for the difference between the two means. If the confidence interval for the mean difference does not contain zero, then the samples are different at the specified level of confidence.

11.3.4.1 Example 1: Confidence Intervals for Means (independent samples)

This example uses data from a Great Basin installation to determine if there are differences in shrub density on shrubland plots between areas that receive training and areas that are unavailable for training (Figure 126). The confidence intervals for the two samples do not overlap and there is some distance between them. In this case we would conclude that the samples are different at a 95% level of confidence; shrub density is higher on plots with no military use.

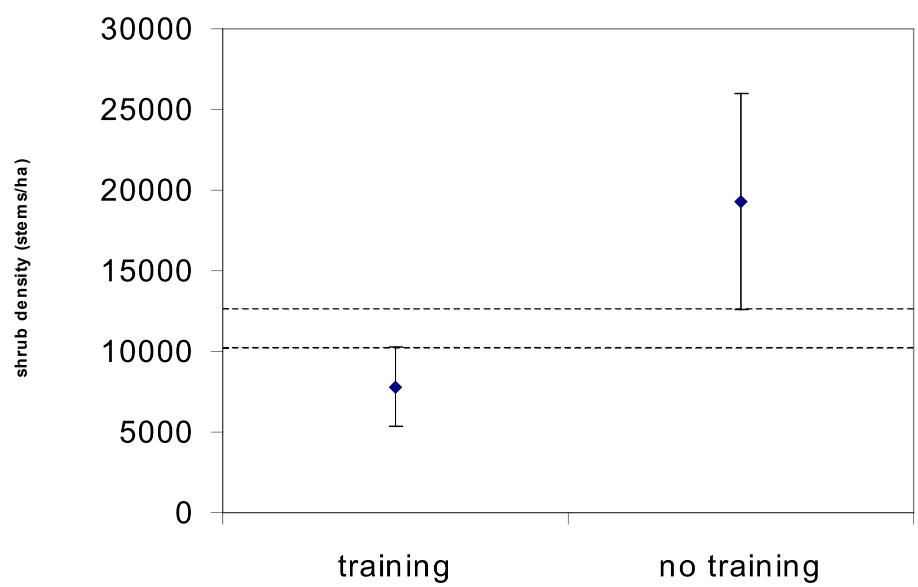


Figure 126. 95% confidence intervals for shrub density on land that is used for military training and land where training is excluded (1991 Idaho data).

11.3.4.2 Example 2: Confidence Interval for the Mean Difference (independent samples)

Using the same data collected at the Idaho site (22 plots in training areas, 22 plots in control areas) in the above example, we can use a more exact approach to examine the difference between two independent samples. Figure 127 illustrates that the 95% confidence interval for the mean difference does not contain zero. We can therefore conclude that the means are different. This result agrees with and provides a less subjective interpretation than the findings based on the comparison of confidence intervals for the sample means (Figure 126).

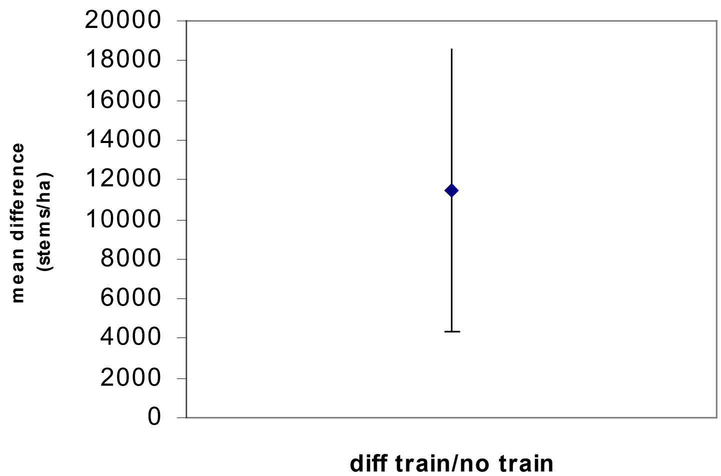


Figure 127. Mean and 95% confidence interval for difference in shrub density in trained and untrained areas, 1991.

11.3.5 Comparing Two Non-independent Samples (permanent plots)

When permanent plots are remeasured, then measurements are not independent from one another. Instead of comparing confidence intervals for point estimates, a confidence interval is constructed around the mean of the differences between each pair of plots using the standard error of the mean difference. This approach is appropriate for examining changes over time. If the confidence interval for the mean difference does not contain zero, then the resampled plots are significantly different at the specified confidence level.

11.3.5.1 Example: Calculate a CI Around the Mean Paired Difference

This example compares data collected from permanent plots (paired data) to determine if there has been a change over time. Data was collected in Idaho on land used for training and adjacent land where no training occurs. Shrub densities were counted on permanent plots in 1991 and 1997. Confidence intervals for the mean difference in shrub densities between 1991 and 1997 were calculated for both types of plots (Figure 128). The results indicate that densities did change significantly (neither confidence interval overlaps with zero). Densities on plots where training occurred increased significantly from 1991 to 1997. Plots located where no training occurs had a significant decrease in shrub density at the 90% confidence level.

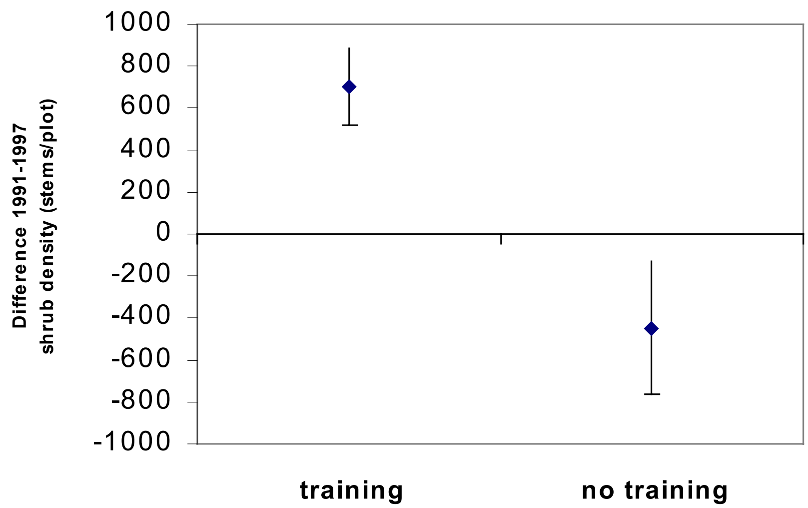


Figure 128. Mean and 90% confidence interval for change in shrub density on permanent plots.

The data can be organized in a simple table based on descriptive statistics that can be calculated by a spreadsheet, a statistical package, or by hand (Table 35).

Table 35. Density of shrubs (live individuals/plot).

		1991		1997		Paired Difference			
	n	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	St. Error	% Diff.
training	22	467.5	332.0	1166.4	918.3	701.4	955.9	111.1	+150
no training	22	1338.9	1243.3	891.9	798.9	-447.0	854.4	182.2	-33

Percent difference is calculated as the change between 1997 and 1991 relative to 1991 (relative change), and is calculated as:

$$\text{relative difference (\%)} = \frac{(\text{1997 mean - 1991 mean})}{\text{1991 mean}} \times 100$$

11.4 Statistical Tests for Monitoring Data

A number of exercises are presented that allow the user to perform technically defensible and statistically sound analyses such as: examination of conditions relative to threshold or 'desired' values, evaluation of the magnitude and significance of changes in resource conditions over time, examination of cause-and-effect relationships, and evaluation of the adequacy of sampling designs using inventory and monitoring data.

11.4.1 Caveats for Statistical Tests

Statistical software makes calculations easy. However, care must be exercised to adhere to the assumptions associated with statistical tests. The primary purpose for statistical tests is to divorce the investigator from bias. Fowler (1990) suggests ways to avoid some common statistical errors:

1. Explain the experimental design and how the statistical analysis was done.

2. Avoid doing lots of separate statistical tests (e.g., do not do a large series of *t*-tests when an ANOVA is appropriate).

3. Be aware of the assumptions associated with the tests used.

4. Don't pool data without justification.

5. Use multiple comparison tests correctly (i.e., if nonsignificance is found in an ANOVA, do not break-up the data to identify significant differences within a subset).

By definition, it is possible to carry out a parametric test if there are at least two samples. With two samples the degree of freedom is 1; however, the quality of the information is questionable (i.e., the sample mean and estimate of variability may not be very representative). The larger the sample size the greater the chance the data represent the population.

Table 36. Statistical terms and their definitions.

Terms	Definition
parameter	A measure of a population, such as the mean, standard deviation, proportion, or correlation.
statistic	A descriptor of a sample, such as mean, standard deviation, proportion, or correlation.
hypothesis	Part of a test for significance is that the hypothesized value of the sample (statistic) is or is not equal to the population (parameter) value.
Type I Error	The null hypothesis is rejected when true. By setting a low level of significance, the chance of a Type I Error is reduced, but the probability of Type II Error increases.
Type II Error	A null hypothesis is accepted when it is false. In this case, the two means really are not equal.
one-tailed test	When a parameter in a hypothesis is stated to be greater than or less than a given value, the test is said to be one-tailed. A one-tailed test considers the results in one direction, such as is μ_1-$\mu_2 > 0$ or biomass is greater on plots with less than 30% tracking. The probability at a given level of significance is half that of a two-tail test, therefore, a one-tail test is more rigorous (powerful) and less susceptible to a Type II error.
two-tailed test	When a parameter in a hypothesis is equal or not equal, then the test is said to be two-tailed. A two-tailed test is preferred if either deviation would be cause for action. In this case, both tails of the sampling distribution are of concern, such as μ_1-$\mu_2 = 0$. The probability at a given level of significance is twice that of a one-tailed test and, therefore, less rigorous.
variable	Any measured characteristic or attribute, such as percent bare ground, litter, or plants/plot.
independent variable	A measured characteristic or attribute thought to be the controlling variable in the relation.
dependent variable	A manipulated characteristic or attribute determined by another variable.
variance	Variance is the measure of variability in a population. The value of a variance around a mean ranges from zero (when all measurements in the population have the same as the mean) to plus infinity (Woolf 1968).

11.4.2 Statistical Significance and Confidence Levels

Statistical significance level and confidence are often used interchangeably. Biological significance is not equivalent to statistical significance. While there is a scientific need for using the terms "significant" or "$P<0.05$", neither may accurately describe a biological significant situation (Yoccoz 1991). While two sample means may differ statistically, the result may be the consequence of a small or unrepresentative sample, nonrandom data, dependency between samples, or unequal variances. For this reason, the importance of incorporating biological meaning or significance into program objectives should not be understated. However, a proper level of biological significance is often difficult to determine. Determining what constitutes a biologically significant change requires reviews of available scientific information and professional judgement. Ideally, significance levels are set prior to looking at the data to avoid bias.

Typically, statistical test results state whether the probability level is greater than or less than the test level (α). In other words, if $\alpha = 0.05$, then the test value is displayed as $P<0.05$ or $P\geq0.05$. One goal of statistical tests is to minimize the chance of committing a Type I error (i.e., rejecting the null hypothesis when it is true - a false change error). By setting $\alpha = 0.20$, there is a greater chance of committing a Type I error. By setting a lower α such as 0.01, there is less chance of committing a Type I error, but a greater chance of committing a Type II error (i.e., accepting the null hypothesis when false; a missed change error).

If change detection is an objective, then particular attention should be paid to setting Type I and Type II error rates. Without a priori information, it may be difficult at the beginning of a monitoring program to set realistic power and Type I error rates simultaneously. One approach is to set Type I and Type II error rates at the same level. The minimum detectable change would be set by the affordable sample size and the observed variance. If the affordable sample size and the minimum detectable change size are unacceptable, then the method or design is inadequate and must be reconsidered (Hinds 1984). Type I and II error rates can also be adjusted (within limits) in order to reach a balance with affordability and minimum detectable change. Sometimes minimum detectable change size and Type II error are ignored altogether while the sensitivity of the analysis to false-change errors is examined exclusively (Hinds 1984).

There is nothing immutable about the values of 0.01, 0.05, and 0.10, which correspond to confidence levels of 99, 95, and 90 percent, respectively (Yoccoz 1991). A biologically significant difference may be accurate at a lower confidence level (e.g., $\alpha = 0.10$ or $\alpha = 0.20$). An $\alpha = 0.20$ may describe a biologically significant difference between a control and training area attribute better than a P value less than an $\alpha = 0.05$. Traditionally, the two types of errors are not treated equally; Type I errors are often considered more severe. For example, a 5% chance of a Type I error and a 20% chance of Type II error may be accepted in relation to a given amount of change (Snedecor and Cochran 1967). In each case, the consequences of making the two errors should be considered. Hinds (1984) suggests that traditional rates for both types of errors of 1 and 5% were suitable for experimental work and domestic (i.e., controlled) conditions where the costs for making errors were quantifiable, and that realistic and adequate error rates for monitoring projects may be significantly higher (10 to 15%) and still produce credible results.

When reporting statistical results include means, a measure of variability (e.g., standard error, standard deviation, confidence interval), the estimated difference set prior to the test (often zero), and the confidence level. Also realize that with further sampling, the probability level and required sample sizes may change. Understanding biological systems requires multiple years of data collection to assess both spatial and temporal variability.

11.4.3 Hypothesis Testing

Hypothesis testing is necessary to correctly interpret statistical results. Some uses of statistics such as confidence intervals do not involve hypothesis testing. Prior to beginning an "experiment," a researcher states the anticipated result or *statistical hypothesis*. Typically, the statement is that a *parameter* (*population*) represented by one *sample* group of data will or will not be equal to a second group of *sample* data. The statement is written about the *population* (*parameter*). The initial hypothesis, or *null hypothesis*, is stated and the *alternative hypothesis*(*es*) follows. A question such as -- *Are military impacts similar between Training Area X and Training Area Y?,* would translate into: *The mean value of the response variable* (e.g., vegetation cover, bare ground) *in areas subjected to training impacts in X equals the mean value of the response variable in areas subjected to training impacts in Y*, or H_o $\mu_1 = \mu_2$, where H_o stands for the null hypothesis, μ_1 is the mean of the population represented by the first sample, and μ_2 represents the mean of the population represented by the second sample. An alternative hypothesis might be: *The mean for the training impacts in X is different from the mean training impact in Y,* or H_1 $\mu_1 \neq \mu_2$.

The basic steps in performing a hypothesis test are:

- State the null and alternative hypotheses.
- Decide on the significance level, α.
- Determine the decision rule.
- Apply the decision rule to the sample data and make the decision.
- State the conclusion in words.

11.5 Choosing a Statistical Procedure

Different monitoring objectives and types of data necessitate that the user choose an analysis approach from a number of possible approaches. Monitoring objectives often focus on parameter estimation and detecting change over time. The selection of a statistical procedure must consider a number of variables, including independence of samples, distribution of data, equality of variances, and type of data. Decision keys for the selection of a statistical procedure for non-independent samples and independent samples are presented in Figure 129 and Figure 130, respectively.

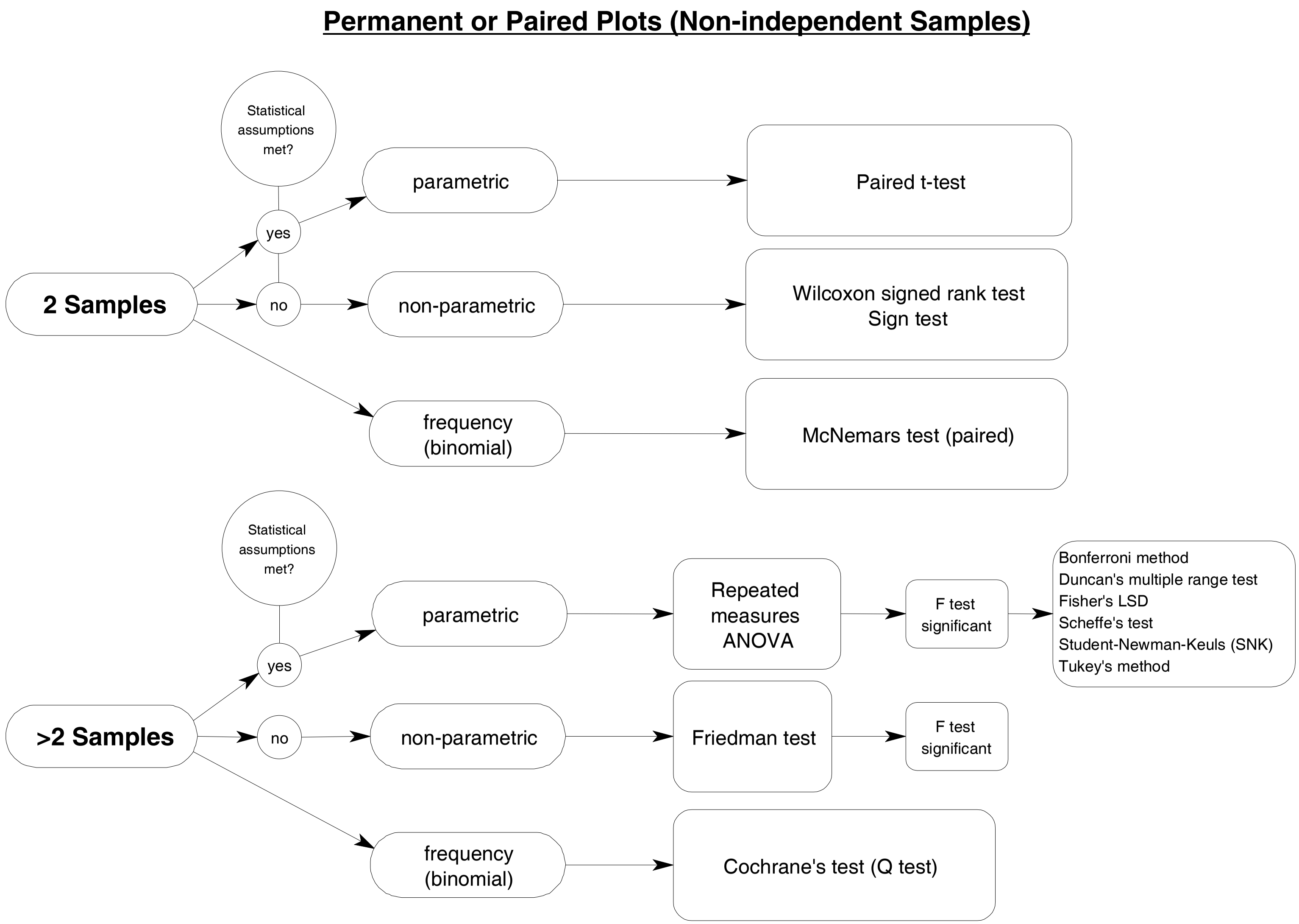


Figure 129. Decision key to statistical analysis of monitoring data from permanent or paired plots.

Temporary Plots (Independent Samples)

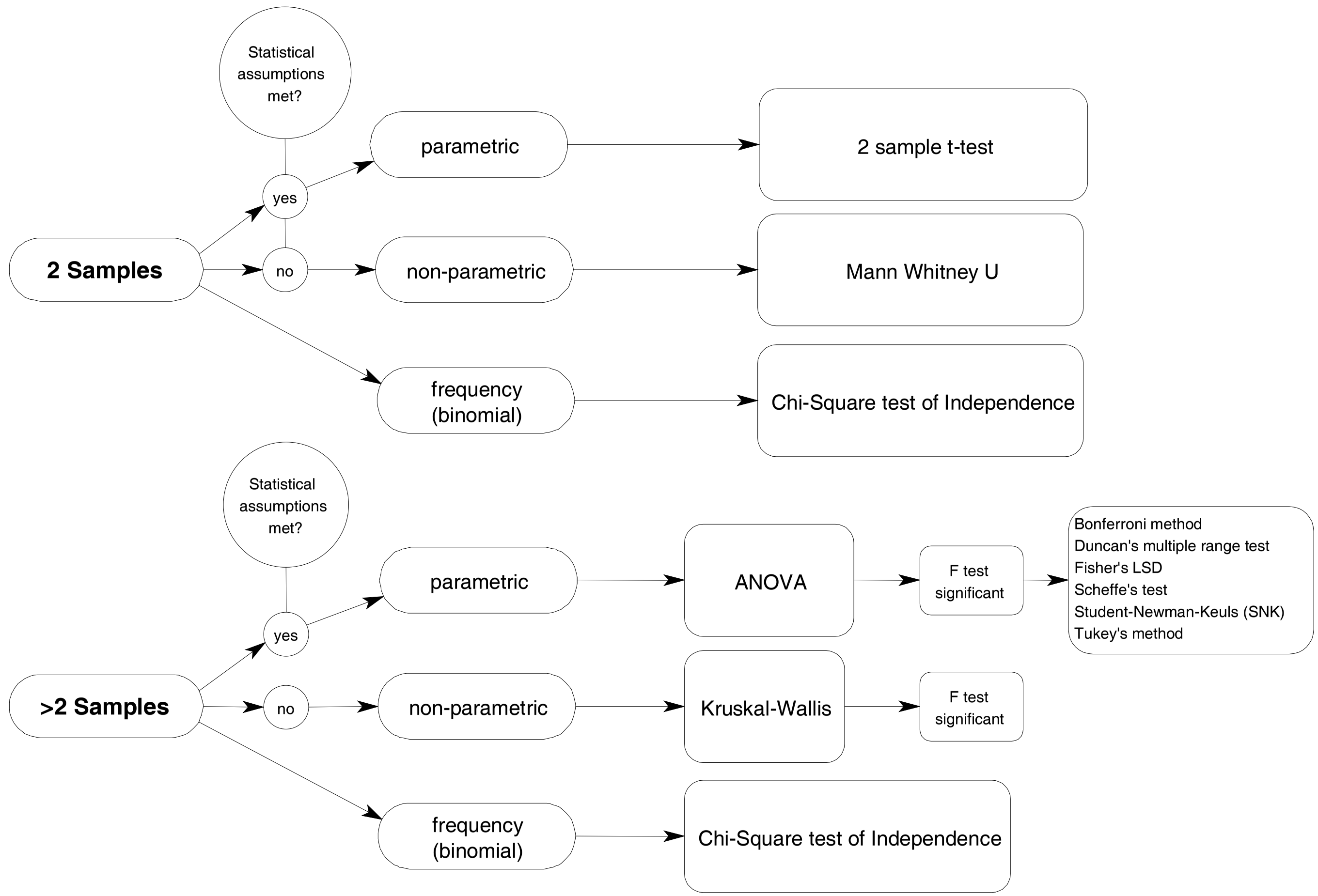


Figure 130. Decision key to statistical analysis of monitoring data from temporary plots.

11.5.1 Normality Assumptions

Examining the normality of sample data involves comparing the distribution of samples to that of a normal distribution. A normal distribution is a specific mathematical function with a bell-like shape, which can be expressed by the mean and the standard deviation. The distribution curve may vary in the height and width; however, the mean, median, and mode are all at the same point. Many biological variables follow a normal distribution. Survivorship curves, rates, and size variables, tend to follow a Poisson or other distribution functions, as do other continuous variables related to time and space. Because the common statistical tests are based on a normal sampling distribution, some investigators test their data for "normality." For these data types, a "goodness-of-fit" test is performed. Goodness-of-fit measures the degree of conformity between the sample data to the hypothesized distribution (D'Agostino and Stephens 1986).

Data can either be graphed or tested to determine if the data approximates a normal distribution pattern. Parametric tests such as an analysis of variance (ANOVA) and *t*-tests assume the data are normally distributed (i.e., a bell shape distribution, or if a cumulative distribution is plotted on normal probability paper, linear). Nonparametric tests do not require a normal data distribution. However, using nonparametric statistics (i.e., rankings) for analyzing continuous data can be problematic, leading to erroneous results. Graphing a data set is a quick method to evaluate the pattern of distribution (Figure 123). Statistical tests are easily performed and included in a number of statistical software packages. Three commonly used tests are the Kolmogorov-Smirnov (KS) test, Pearsons Chi-Square, and Log-likelihood ratio.

When data do not conform to a particular probability distribution, there are two courses of action. The first is the use of a nonparametric test, such as Kruskal-Wallis or Friedman. A second possibility, is to transform the variable to meet the assumption of normality (Sokal and Rohlf 1981). By transforming the data to another scale, a standard analysis can be used. An appropriate transformation may be a logarithmic scale for data that are multiplicative on a linear scale. The use of square root transformation works well for areas, reciprocals for pH and dilution series, and arcsine transformation for percentages and proportions. Scale of measurement is arbitrary and transformation of the variable helps satisfy the assumptions of parametric tests (Sokal and Rohlf 1981).

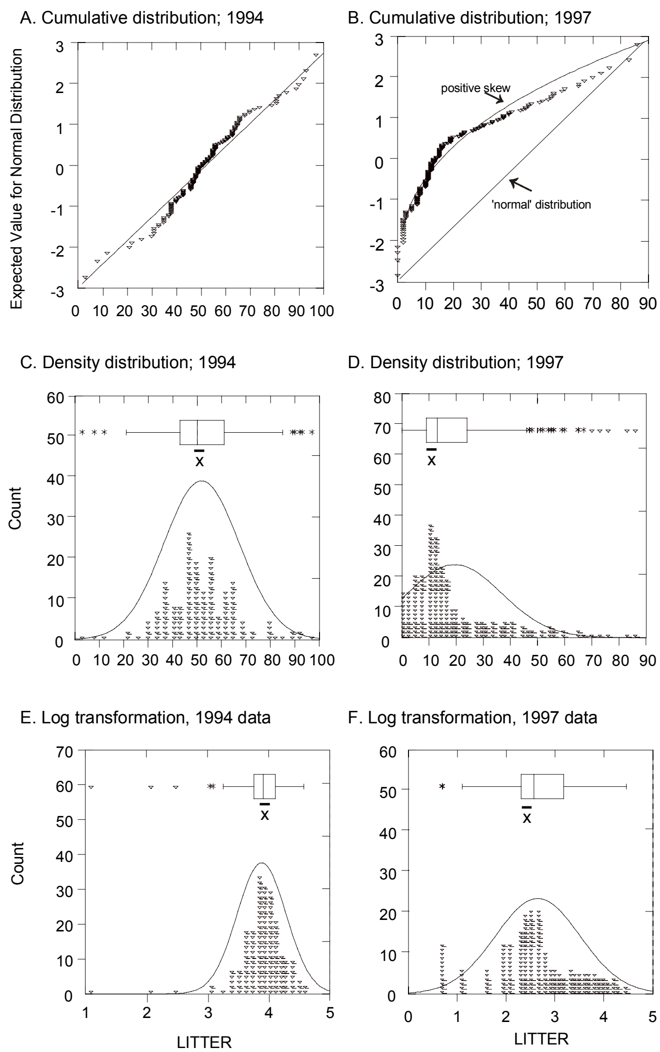


Figure 131. Comparison of differences in cumulative, density, and log-transformed density distribution of litter ground cover; 1994 and 1997.

A. Linearity of cumulative distribution as an estimation of normality of data in 1994. B. Lack of linearity of cumulative distribution of data in 1997, suggesting nonnormality. C. Density distribution of 1994 data approximates a Gaussian, or bell-shape distribution. D. Positive skew of the density distribution of the data in 1997, suggesting nonnormality. The box at the top of graphs C and D are the confi**dence intervals. The means are shown ($\bar{x}$). E and F. Log transformations.**

11.5.2 Frequency/Binomial Tests

The chi-square test of independence and McNemar's test are nonparametric tests for detecting differences between proportions. Discussion and examples of these tests are provided in section 11.5.4, Non-paramentric Tests.

11.5.3 Parametric Tests

Parametric tests involve the calculation of the *t* statistic (i.e., the sample average divided by the estimated standard error, or the number of estimated sample standard deviations the test statistic ($\bar{x}$) is from its hypothesized value) or the *F* statistic (i.e., Treatments Mean Square divided by Error Mean Square). In both cases, the parameter of interest is the population mean (μ). Because the value of μ is reflected in the sampling distribution of $\bar{x}$ (sampling mean), and because $\bar{x}$ follows a normal distribution with a sufficient sample size, the *t* and *F* tests are good tests for identifying differences between and among sample means.

11.5.3.1 The T-Test

A *t*-test is a measure of a random sample mean and an unbiased estimate of a population. The sampling distribution of the data set should be normal, or a close approximation. *t*-tests, and other parametric tests are not as robust with small sample sizes (e.g., less than 12) as they are with larger samples (e.g., 100 or more). The larger the sample size the closer the sample distribution approaches to a normal distribution. Large samples are robust (i.e., there is a greater chance the P value is accurate), powerful (i.e., correctly rejecting a false null hypothesis, or 1- β), and can discriminate between a normal and a non-normal distribution (GraphPad 1998). Small samples often do not have enough information and, in some cases, statistical testing may be inappropriate.

The generalized formula for a *t*-test is (Rice Virtual Lab 1998):

$$t = \frac{Statistic - Hypothezised\ value}{\text{Estimated standard error of the statistic}} \quad \text{OR} \quad t_{df=n-1} = \frac{\bar{x} - \mu_h}{\sqrt{\frac{s_x^2}{n}}}$$

where $\bar{x}$ = the mean of the random sample
μ_h = the statistical hypothesis of the population mean
s_x^2 = the estimated population variance
n = sample size

A typical null hypothesis associated with a *t*-test is stated as the mean equal to zero (H_o $\bar{x} = 0$), or any other value. The value should represent a target or threshold that has real-world significance. For example, if we want warm season grass cover to be at least 30%, then we would state the null hypothesis as H_o $\bar{x} \geq 30\%$. In this case a one-tailed test would be employed. The alternative hypothesis may be the mean does not equal a value (H_1 $\bar{x} \neq 0$) or that the mean of the population is greater than a given value (H_o $\bar{x} > 0$). If the alternative hypothesis is H_1 $\bar{x} \neq 0$, then a two-tailed test of significance is required. If the alternative hypothesis is H_1 $\bar{x} > 0$, then a one-tailed test of significance is appropriate. The difference is whether or not both or only one side of the normal curve is considered by the test. When a hypothesis states greater than or less than, only one-tail of the curve is considered. When a hypothesis states a condition either equal to or unequal to some value then both tails of the curve must be considered (two-tailed test).

11.5.3.1.1 One Sample T-Test Example

Consider plant litter estimated on ten plots and from each plot determine the difference X_I from μ when $\alpha = 0.05$ (Table 37). The previous year, litter ground cover was estimated at 25%. We want to know if litter cover this year is significantly different from 25% The null hypothesis is $H_o\ \mu = 25$ (i.e., the average amount of litter ($\bar{x}$) represented by the sample is equal to or greater than the threshold value specified for the population). The alternative is H_1 , $\mu \neq 25$.

Table 37. Percent litter cover for 10 samples.

Statistical Parameter	X_i	X_i^2
	43	1,849
	58	3,364
	62	3,844
	24	576
	29	841
	33	1,089
	34	1,156
	85	7,225
	26	676
	42	1,764
Sum of the percent litter on 10 plots = $\sum X_I$	436	
Sample mean = $\sum \frac{X_i}{n}$ where n = the sample size	43.6	
Sum of each sampled squared = $\sum X_i^2$		22,384

$$\text{Sample variance} = s^2 = \frac{\sum (X_i - \bar{x})^2}{n-1} = \frac{\sum X_i^2 - \frac{(\sum X_i)^2}{n}}{n-1}$$

$$= \frac{22{,}384 - \frac{(436)^2}{10}}{10-1}$$

$$= \frac{22{,}384 - 19009.6}{9}$$

$$= 374.9$$

$$\text{Standard deviation (s)} = \sqrt{s^2} = \sqrt{374.9} = 19.36$$

$$\text{Estimated standard error} = s_{\bar{x}} = \sqrt{\frac{s^2}{n}} = \sqrt{\frac{374.9}{10}} = 6.12$$

Calculated *t value* $\quad t = \frac{\bar{x} - \mu}{s_{\bar{x}}} = \frac{43.6 - 25}{6.12} = 3.04$

The estimated sample mean ($\bar{x}$) is 43.6, the hypothesized population mean is 25, and the standard error ($s_{\bar{x}}$) is 6.12, and the calculated *t* is +3.04. The critical *t* value for 10-1 = 9 degrees of freedom at P (0.05) is 2.26 and for P (0.01) is 2.82 (see Table 71, Critical Values of the Two-tailed Student's T-Distribution). Because the calculated t is greater than the critical t value, we reject the null hypothesis. The probability value for the calculated *t* is therefore smaller than 0.01. If only one tail of the curve is considered, and the alternative hypothesis is H_1 $\mu \geq 25$, the probability at 0.05 would be half the stated *t*-value or 1.13 and 1.41 for P (0.01).

To set the confidence limits at 95% for the population mean from which the sample was drawn, the *t* value at the 0.05 level for *n* - 1 degrees of freedom is 2.26.

$L_1 = \bar{x} - t_{0.05}\ s_{\bar{x}} = 43.6 - 2.26(6.12) = 29.77$

$L_2 = \bar{x} + t_{0.05}\ s_{\bar{x}} = 43.6 + 2.26(6.12) = 57.43$

The probability is 95% that the true population mean is between 29.77 and 57.43.

Confidence limits are useful measures of the reliability of a sample statistic, but are not commonly stated in scientific publications. Generally, the statistic plus and minus (+/-) its standard error are cited along with the sample size upon which the standard error is based (Sokal and Rohlf 1981). However, in monitoring, confidence intervals are very useful for comparing a mean to a threshold or target value. If the target value fall outside the confidence interval, then you can be 1-α % confident that the mean is greater than, less than, or no different from the threshold value, whatever the case may be.

Statistical books have additional examples. The primary source used for this discussion was *Principles of Biometry* by C. M. Woolf (1968).

11.5.3.1.2 Comparison Test Involving Two Sample Means

A common test is to compare sample means from random samples. If $\mu_1 = \mu_2$, i.e., the samples means are the same, then any differences are due to sampling variation. The point at which the samples describe different populations is based on the level of significance set prior to the test (e.g., $\alpha = 0.05$).

A group comparison test requires the samples to be independent, normally distributed, and to have equal population variances. The null and alternative hypotheses are: H_o $\mu_1 = \mu_2$ and H_1 $\mu_1 \neq \mu_2$. The degrees of freedom are $(n_1 - 1) + (n_2 - 1)$. The alternative hypothesis calls for a two-tailed *t*-test. For the following question, the significance level is $\alpha = 0.05$.

Given plant litter cover data was estimated on an installation in June and September of the same year, do the means represent the same population (H_o $\mu_1 = \mu_2$)? or the alternative hypothesis -- do the means represent different populations (H_1 $\mu_1 \neq \mu_2$), $\alpha = 0.05$ (Table 38)?

Table 38. Plant litter cover data collected across an installation in June and September 1998.

	June		September	
	X_1	X_1^2	X_2	X_2^2
	58	3364	27	729
	61	3721	22	484
	54	2916	4	16
	54	2916	17	289
	52	2704	19	361
	44	1936	19	361
	87	7569	32	1024
	71	5041	33	1089
	65	4225	32	1024
	71	5041	42	1764
	82	6724	37	1369
	62	3844	22	484
	53	2809	25	625
	40	1600	33	1089
	66	4356	33	1089
	20	400	16	256
	52	2704	16	256
	52	2704	40	1600
	58	3364	17	289
	34	1156	14	19
	65	4225	30	90
	44	1936	25	62
	48	2304	25	62
	69	4761	30	90
	48	2304		
	74	5476		
	74	5476		
	35	1225		
	53	2809		
	77	5929		
$\sum x_i$	1723		610	
$\sum x_i^2$		105,539		17
$\bar{x}_i$	57.4		25.4	
n_i	30		24	

The formula for the estimated pooled variance is:

$$s_p^2 = \frac{\sum X_1^2 - \frac{(\sum X_1)^2}{n_1} + \sum X_2^2 - \frac{(\sum X_2)^2}{n_2}}{(n_1 - 1) + (n_2 - 1)}$$

$$= \frac{\left[105{,}539 - \frac{2{,}968{,}729}{30}\right] + \left[17{,}444 - \frac{372{,}100}{24}\right]}{(30-1)+(24-1)}$$

$$= \frac{6{,}581.4 + 1{,}939.8}{52}$$

= 163.87

The calculated *t* value is -- $= \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{s_P^2 \left(\frac{1}{n_1}\right) + \left(\frac{1}{n_2}\right)}} = \frac{57.4 - 25.4}{\sqrt{16387*(29+23)}} = 9.13$

Since $\alpha = 0.05$, the corresponding *t* statistic is between 2.00 and 2.02 for 52 degrees of freedom. Because *t* is greater than 2.00 and 2.02, the null hypothesis is rejected, or $P<0.05$ for 52 df; that is, the difference in litter cover between June and September is statistically significant.

The confidence intervals based on the pooled variance for the individual population means at 95% are:

$$\mu = \bar{x} \pm t_{0.05} \sqrt{\frac{s_p^2}{n_i}}$$

$$\mu_1: \ \mathrm{L}_1 = 57.43 - 2.01\sqrt{\frac{163.87}{30}} = 52.7$$

$$\mathrm{L}_2 = 57.43 + 2.01\sqrt{\frac{163.87}{30}} = 62.1$$

$$\mu_2: \ \mathrm{L}_1 = 25.42 - 2.01\sqrt{\frac{163.87}{24}} = 20.2$$

$$\mathrm{L}_2 = 25.42 + 2.01\sqrt{\frac{163.87}{24}} = 30.7$$

The confidence intervals can be determined using individual variances for each mean rather than the pooled variance; however, the pooled variance is a better estimator of the population's variance.

11.5.3.1.3 Paired T-Test

When samples are not independent and when there is a positive correlation between the two sample means, a paired design is appropriate. Also, a paired test requires equal sample sizes. There is no assumption that the variances are equal; however, the differences between the samples should have a consistent variance (i.e., the variance of the differences does not increase as the differences themselves increase).

Given percent litter ground cover was determined on plots both in June and September, do the means represent the same population (H_o $\mu_1 = \mu_2$) or, the alternative hypothesis, do the means represent different populations (H_1 $\mu_1 \neq \mu_2$) at $\alpha = 0.05$ (Table 39).

Table 39. Litter ground cover data collected at 30 permanent plots in June and September.

	Plot	June	September	Difference	
				d	d^2
	1	58	27	31	961
	2	61	22	39	1521
	3	54	4	50	2500
	4	54	17	37	1369
	5	52	19	33	1089
	6	44	19	25	625
	7	87	32	55	3025
	8	71	33	38	1444
	9	65	32	33	1089
	10	71	42	29	841
	11	82	37	45	2025
	12	62	22	40	1600
	13	53	25	28	784
	14	40	33	7	49
	15	66	33	33	1089
	16	20	16	4	16
	17	52	16	36	1296
	18	52	40	12	144
	19	58	17	41	1681
	20	34	14	20	400
	21	65	30	35	1225
	22	44	25	19	361
	23	48	25	23	529
	24	69	30	39	1521
	25	48	24	24	576
	26	74	40	34	1156
	27	74	11	63	3969
	28	35	11	24	576
	29	53	8	45	2025
	30	77	39	38	1444
$\bar{x}_i$		57.43	24.76	32.66	
$\sum X_d$				980	
$\sum X_d^2$					36930
n_d	30				

The variance of the sample differences is --

$$s_p^{\ 2} = \frac{\sum X_d^{\ 2} - \frac{\sum (X_d)^2}{n_d}}{n_d - 1}$$

$$= \frac{36{,}930 - \frac{(980)^2}{30}}{30 - 1}$$

$$= \frac{36{,}930 - 32{,}013.3}{29}$$

$$= 169.5$$

The estimated standard error of the mean difference is --

$$s_{\bar{x}d} = \sqrt{\frac{s_d^{\ 2}}{n}} = 2.38$$

The t value is --

$$t = \frac{\bar{x}_d}{s_{\bar{x}d}} = 13.7$$

The t value is greater than the critical t value for $\alpha = 0.05$; therefore $P<0.05$ for 29 degrees of freedom. The null hypothesis is rejected (*The means represent the same population*, H_0 $\mu_1 = \mu_2$) and the alternative hypothesis is accepted (*The means represent different populations,* H_1 $\mu_1 \neq \mu_2$).

The 95% confidence interval is 27.8 to 37.5.

11.5.3.2 Analysis of Variance (ANOVA)

When more than two samples are compared, an Analysis of Variance (ANOVA) is an appropriate parametric test. The ANOVA table accounts for the variation of selected factors of numerous samples simultaneously. ANOVAs are often used to compare the effectiveness of different management activities or other applied treatments, for example as in experimental designs. The experimental design chosen will determine how the ANOVA table is constructed. Differences in the primary factors of interest can be examined by removing variability in the data that can be attributed to other factors (e.g., natural variability). ANOVAs can also be applied when comparing conditions or measured variables in three or more management units or geographical areas, even if differences in treatments, stressors, or land uses are unknown.

11.5.3.2.1 ANOVA Example

We want to test for differences among groups (or treatments) using ANOVA and a post-hoc multiple comparison procedure.

Data were collected at 5 different training sites (locales) within the same soil type (Table 40). Cone penetrometer readings were taken to indicate the degree of surface soil compaction. Shallow penetration depths indicate increased compaction. A one way analysis of variance was performed to test the hypothesis that the sample means for the five sites are not different from one another.

Table 40. Raw soil surface compaction data.

SITE	SAMPLE	DEPTH	SITE	SAMPLE	DEPTH
1	1	6.9		6	6.6
	2	7.3		7	5.6
	3	6.5		8	5.6
	4	7.2		9	5.8
	5	6.7		10	5.9
	6	7.9	4	1	6.7
	7	6.4		2	7.0
	8	6.6		3	8.9
	9	5.6		4	7.1
	10	8.1		5	5.5
2	1	7.7		6	6.6
	2	5.6		7	5.9
	3	7.6		8	7.0
	4	6.4		9	5.8
	5	8.5		10	5.3
	6	5.5	5	1	5.3
	7	7.0		2	6.2
	8	7.8		3	6.9
	9	7.4		4	6.7
	10	7.2		5	5.7
3	1	5.3		6	4.6
	2	5.5		7	5.3
	3	5.9		8	6.9
	4	6.3		9	5.6
	5	5.8		10	6.5

The F-ration in the ANOVA table is used to test that hypothesis that the slope is zero. The F is large (between group error is much larger than within group error) when the independent variable helps to explain the variation in the dependent variable. Here there is a significant linear relationship between compaction and site. Thus we reject the hypothesis that the slope of the regression line is zero. The ANOVA results indicate that at the 0.05 level of significance, the means for the five sites are not all the same (P value = 0.0034<0.05) (Table 41).This type of test is similar to doing a number of t-tests, but is more powerful because the variances are pooled. Once the ANOVA is completed, a multiple pairwise comparison can be performed to determine which site (or sites) is different from the others. In this case, the Bonferroni procedure was applied at a 95% confidence level (see section 11.5 for a discussion of procedures). The matrix of pairwise comparison probabilities reveals several significant differences among sites (Table 42). The Bonferroni test results indicate significant differences between sites 1 and 3, sites 2 and 3, and sites 2 and 5.

Table 41. One-way ANOVA results using compaction data.

Source	Sum-of-Squares	df	Mean-Square	F-ratio	P
SITE (between groups)	12.3412	4	3.0853	4.6011	0.0034
Error (within groups)	30.1750	45	0.6706		

Table 42. Matrix of pairwise comparison probabilities from a Bonferroni test. Significant pairwise differences at α=0.05 are highlighted (P<0.05). Means with the same letter in the summary column are not significantly different.

SITE	1	2	3	4	5	MEAN	Summary
1	1.0000					6.92	ac
2	1.0000	1.0000				7.07	a
3	0.0468	0.0148	1.0000			5.83	bd
4	1.0000	1.0000	0.4642	1.0000		6.58	ab
5	.1275	0.0435	1.0000	1.0000	1.0000	5.97	cd

11.5.3.3 Correlations and Regression

Correlation and regression analyses test the relationship and the degree of relationship of two variables to each other. In correlation analysis, variables are independent of each other. In regression analysis, the two variables may consist of one independent (i.e., a fixed variable by the investigator) and one dependent (Model I), or each variable may be independent of the other (i.e., without investigator control) (Model II). The difference between a Model II regression and correlation analysis is the lack of units in correlation analysis. With regression analysis, the X and Y variables are compared based on their units. Both tests will indicate whether a relationship exists between two variables, but using different ways (Woolf 1968).

Regression and correlation analyses are two different tests. While many of the calculations are similar, each addresses a very different question. In regression analysis, the intent is to examine the possible causation of changes in Y by changes in X for purposes of prediction and to explain variation. Causation of change is unknown in correlation analysis, rather the question is how much do the variables vary together (covariance) (Sokal and Rohlf 1981)? There may be a relationship between the variables examined by correlation analysis, but the mathematical model for that relationship is not of direct concern.

Biological variables generally have a relationship to other variables. For example, litter cover is noted on a series of plots with varying levels of tracked vehicle use. The differences in litter cover may or may not be aligned with training activities. If differences in litter cover are related to training actives, to what degree? In this case, litter cover would be the dependent variable and the amount of training the independent variable. The type of analysis could be either correlation or regression analysis. If on the other hand, if we pose the question: *Is there a relationship between the amount of litter cover and the amount of standing biomass on training lands?*, then correlation or Model II regression analysis would be appropriate. A Model II regression would consider each variable as independent (i.e., without investigator control).

A scatter diagram is a pictorial method of describing the relationship of two variables (Figure 4.4-4). If there is no correlation between the two variables, the line that best fits the scatter of points is horizontal. With a positive correlation, the slope of the line increases as each variable increases, and with a negative correlation, as one variable increases, the second decreases. In some cases, a curved line is the best fit. Only linear relationships will be discussed here.

Figure 132. The correlation between two variables can be none, positive (as one variable increases so does the other), or negative (as one variable increases the other decreases).

Fitting a line to a scatter of data can lead to a bias interpretation of the data. An objective method used in regression analysis is least squares; that is, fitting a line through points that is the minimum value of the summation of the squared deviations (Woolf 1968).

11.5.3.3.1 Regression Example

The following example compares output for a regression analysis computed with MS Excel (Tool, Data analysis, Regression) with a step-by-step presentation of the calculation of the same information.

On a military installation, areas are subjected to varying amounts of tracked vehicle impacts. We pose the following question: *Is there a relationship between the amount of litter and the amount of tracked vehicle use* (Table 43)?

The question can be addressed by using regression (Model I -- one variable is dependent on a second variable) or by correlation analysis. The null hypothesis is H_o $\beta=0$, and the alternative hypothesis is H_1 $\beta\neq0$. There are some assumptions involved: 1) the amount of litter within each level of tracked vehicle intensity follows a normal distribution, and 2) the variances of the populations represented by the various intensities are equal.

Table 43. Training intensity recorded as percent tracked vehicle disturbance and percent plant litter cover on 15 plots.

PlotID	Training Intensity		Litter Cover		
Samples	X_i	X_i^2	Y_i	Y_i^2	$X_i Y_i$
1	23	529	80	6400	1840
2	28	784	78	6084	2184
3	22	484	65	4225	1430
4	29	841	67	4489	1943
5	35	1225	53	2809	1855
6	42	1764	58	3364	2436
7	43	1849	52	2704	2236
8	48	2304	49	2401	2352
9	39	1521	46	2116	1794
10	54	2916	35	1225	1890
11	52	2704	38	1444	1976
12	61	3721	32	1024	1952
13	72	5184	23	529	1656
14	68	4624	34	1156	2312
15	83	6889	29	841	2407
n=15	$\sum X_i$=699		$\sum Y_i$=739		$\sum X_iY_i$=30263
	$\bar{x}$=46.6		$\bar{y}$=49.3		
		$\sum X_i^2$=37339		$\sum Y_i^2$=40811	

$$\sum x^2 = \sum X_i^2 - \frac{(\sum X_i)^2}{n} = 37{,}339 - \frac{(699)^2}{15} = 4{,}765.6$$

$$\sum y^2 = \sum Y_i^2 - \frac{(\sum Y_i)^2}{n} = 40{,}811 - \frac{(739)^2}{15} = 4{,}402.9$$

$$\sum xy = \sum X_i Y_i - \frac{(\sum X_i)(\sum Y_i)}{n} = 30{,}2063 - \frac{(699)(739}{15} = -4174.4$$

The regression coefficient: $$b = \frac{\sum xy}{\sum x^2} = \frac{-4{,}174.4}{4{,}765.6} = -0.88$$

It is estimated that for a 1 unit increase in tracked vehicle use there is an 0.88 percentage point decrease in litter.

If the value *b* is known, then *a* from the equation for a slope ($a = \bar{y} - b\bar{x}$) can be determined (Table 44).

$a = \bar{y} - b\bar{x}$ = 49.3-(-0.88)(46.6) = 90.09

Table 44. The difference between the observed and the estimated litter ground cover.

PlotID	Training Intensity	Litter Cover – Observed	Litter Cover -- Estimated	$Y - \hat{Y}$	$Y - \hat{Y}^2$
samples	X	Y	$\hat{Y}$	d	d^2
1	23	80	69.9	10.1	101.22
2	28	78	65.6	12.4	154.77
3	22	65	70.8	-5.8	33.81
4	29	67	64.7	2.3	5.37
5	35	53	59.4	-6.4	41.31
6	42	58	53.3	4.7	22.13
7	43	52	52.4	-0.4	0.18
8	48	49	48.0	1.0	0.92
9	39	46	55.9	-9.9	98.48
10	54	35	42.8	-7.8	60.60
11	52	38	44.5	-6.5	42.73
12	61	32	36.7	-4.7	21.65
13	72	23	27.0	-4.0	16.14
14	68	34	30.5	3.5	12.10
15	83	29	17.4	11.6	134.97
		Sum =739	Sum =739	Sum = 0.0	Sum = 746.39

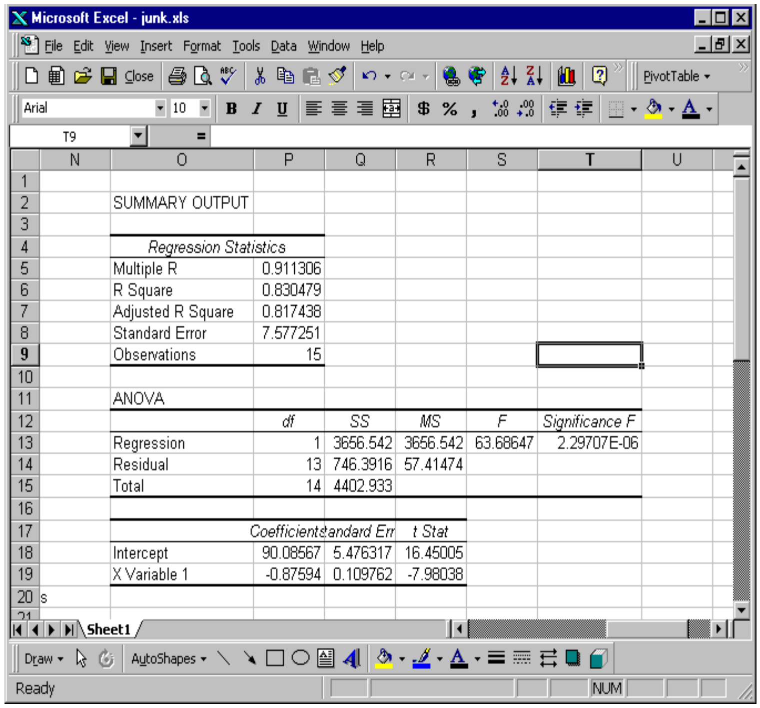
Where $\hat{Y} = a + bX$ = 90.09 + (-0.88)*X*.

For PlotID 1 $Y - \hat{Y}$ = 90.09 + (-0.88)(23) = 10.1

The sum of $(Y - \hat{Y})^2$ is also referred to as the *error sum of squares* or d^2. The variance is:

$s_{xy}^2 = \sum (Y - \hat{Y})^2 / n\text{-}2$ = 746.4/13 = 57.41

From these calculations an analysis of variance table for a regression analysis can be filled.



If a statistical package is used, only the results are displayed. MS Excel includes the ANOVA table and how the variance is partitioned is shown in the output. In most cases, a *t* test is all that is necessary to determine which hypothesis is appropriate.

$\sum y^2$ = Total sum of squares (Total)
= 4402

$\sum d^2$ = Error sum of squares (Residual)
= 746.4

$\sum \hat{Y}^2$ = Regression sum of squares
(Regression) is the difference between the $\sum y^2$ and $\sum d^2$

$$= \sum y^2 - \sum d^2 = 3656.5$$

The degrees of freedom (*df*) are 1 for the Regression, 13 for the Residual (n-2), and 14 for the total (n-1). The Mean Squares are calculated for the Regression and the Error (Residual) by dividing the sum of squares by the degrees of freedom.

The F-value is the Regression Mean Square divided by the Error Mean Square, or

$F = 3656.5/57.4 = 63.69$

Since $F[^{1}_{13}0.05] = 4.7$ (look up in an F table), the null hypothesis would be rejected. A negative relationship does exist between training intensity (tracked vehicles) and litter cover.

The t-value can be calculated a number of ways. One way is to divide the regression or b by the standard error, or

$$t = \frac{b}{\sqrt{\frac{s_{xy}{}^2}{\sum x^2}}} = \frac{-0.876}{\sqrt{\frac{57.4}{4{,}765.6}}} = -7.98$$

The probability of t at 0.05 is 2.16; therefore $P<0.05$ for 13 degrees of freedom.

11.5.3.3.2 Correlation Example

While MS Excel includes the correlation coefficient and the coefficient of determination as part of the regression analysis output, these two values are the products of correlation and not regression analysis. The values used to calculate the correlation coefficient, however, follow the steps for regression. The correlation coefficient (Multiple R as identified in MS Excel) is --

$$r = \frac{\sum xy}{\sqrt{(\sum x^2)(\sum y^2)}} = \frac{-4{,}174.4}{\sqrt{(4{,}765.6)*(4{,}402.9)}} = -0.911$$

The coefficient of determination (R^2) is --

$r^2 = 0.8305$

In other words, approximately 83.05% of the variance in Y (litter) can be attributed to X (training intensity). If 83.05% of the variation in Y is due to the linear regression of Y on X then 16.95% remains unexplained. A table of critical values for correlation coefficients is presented in Table 72 (Section 11.15 - Statistical Reference Tables).

11.5.4 Non-Parametric Tests

Parametric tests are based on assumptions, such as a random sample and equal variances. While an investigator may presume the data meet these assumptions, data are rarely examined prior to the execution of the desired test. These and other assumptions associated with parametric tests are very stringent. Often assumptions are presumed to be met due to sample size alone. There are instances when it is apparent the assumptions will not be met. These include a small number of samples and a non-normal data distribution. In these cases, nonparametric tests may be appropriate.

Also known as *distribution-free methods,* non-parametric tests are not concerned with specific parameters, such as the mean in an analysis of variance (ANOVA), but the distribution of the variates (Sokal and Rohlf 1981). Nonparametric analysis of variance is easy to compute and permits freedom from the distribution assumptions of an ANOVA (i.e., the data may or may not follow a Gaussian, bell shape distribution). These tests are less powerful than parametric tests when the data are normally distributed. In such cases, P values tend to be higher, and there is a greater possibility of making a Type II error (Woolf 1968). As with parametric tests, the larger the sample size, the greater the power of a nonparametric test.

Some guidelines for deciding when to apply a nonparametric test (GraphPad 1998):

1) Fewer than 12 samples.
2) Some values are excessively high or low.
3) The sample is clearly not normally distributed. Consider transforming the data to convert from non-normal to a normal distribution and then using a parametric test.
4) A test for normality fails. Be aware that testing for normality requires a dozen or more categories to be effective.

Keep in mind that nonparametric tests are counterparts to parametric tests (Table 45).

Table 45. Nonparametric test equivalents of parametric tests.

PARAMETRIC TESTS	NONPARAMETRIC EQUIVALENTS
Student's *t*-Test	Kolmogorov-Smirnov, One-Sample
Group Comparison	Multi-Response Permutation Procedure Kruskal-Wallis *H* Mann-Whitney*U* Kolmogorov-Smirnov, Two-Sample Wilcoxon Signed Rank, Not Paired
Paired *t*	Wilcoxon Signed Rank, Paired
Two-way ANOVA; Randomized-Block	Friedman X_r^2
Correlation	Spearman Rank-Correlation Coefficient Kendall Rank-Correlation

Another consideration for choosing between a parametric and a nonparametric test is the type of scale used. Data based on descriptive scales (e.g., nominal scales -- short, tall;

ordinal scales -- short, medium, tall, very tall; and some interval scales that may not meet the assumptions of normal distribution or homogeneous variances) should be tested using nonparametric tests. Data described by an interval scale and interval scales with a true zero point (a ratio scale), should be examined with parametric tests if the test assumptions are met (Woolf 1968).

The chi-square test and McNemar's test are presented below. Both can be calculated using statistical software programs that provide P values to directly determine statistical significance.

11.5.4.1 Chi-Square Test of Independence

The chi-squared test of independence is used to determine if there is an association or statistical dependence between two characteristics of a population. It is appropriate for determining a change in frequency (proportion) when using temporary sampling units or comparing differences in two or more samples at a given point in time. This test can be used where quadrats (frequency sampling) or points (point intercept sampling) are the sampling units and data is not consolidated to the "plot" level. Actual frequency counts, not percentages, are the unit of measurement used by the chi-square test.

In the example presented below (Table 46), the level of tracked vehicle use on different slopes was categorized as either high or low. The data can be used to address the question: *is there a relationship between intensity and slope steepness*? Based on that question, null and alternative hypotheses were developed:

Null hypothesis (H_o): amount of tracked vehicle use is independent of slope steepness
Alternative hypothesis (H_a): amount of tracked vehicle use is dependent on slope steepness.

The test compares observed frequencies with the frequencies that would be expected if the null hypothesis of independence were true. The test statistic employed to make the comparison is the chi-square statistic (X^2):

$$X^2 = \frac{\sum (O-E)^2}{E}$$

where O = observed frequency, and E = expected frequency

The observed frequency is the value recorded during data collection. The expected frequency is calculated with the following equation:

$$\text{Expected frequency} = \frac{\text{row total} * \text{column total}}{\text{sample size}}$$

Contigency tables are used to organize and analyze frequency (or binomial) data (Table 46). Contingency tables are based on the concept that rows and columns are independent. The simplest contingency table is made up of 2 columns and 2 rows (2x2).

Table 46. Qualitative data for tracked vehicle use on slopes.

	Slopes < 25%	Slopes > 25%	**Totals**
High Tracked Vehicle Use	23	2	25
Low Tracked Vehicle Use	4	21	25
Totals	27	23	50

The data in the table suggest that there is a tendency for a tracked vehicle use to be higher on shallower slopes than on steeper slopes. To test the hypothesis of the independence of the rows from the columns, it is necessary to determine the *expected frequency* (*E*) for the four cells. Results are presented in Table 47. For the first cell, the expected value is:

$$E = \frac{25 \text{ x } 27}{50} = 13.5$$

Table 47. The observed and the expected frequency of tracked vehicle use in relation to slope steepness. Expected values are in parentheses.

	Slopes < 25%	Slopes > 25%	**Totals**
High Tracked Vehicle Use	23 (13.5)	2 (11.5)	25
Low Tracked Vehicle Use	4 (13.5)	21 (11.5)	25
Totals	27	23	50

The Chi-Square test is used to test the independence of the variables:

$$\chi^2 = \frac{(23-13.5)^2}{13.5} + \frac{(2-11.5)^2}{11.5} + \frac{(4-13.5)^2}{13.5} + \frac{(21-11.5)^2}{11.5} = 29.06$$

This chi-square value of 29.06 is compared to the chi-square value obtained from a table of critical chi-square values (Section 11.15 Appendix – Statistical Reference Tables). The degrees of freedom for determining the critical chi-square value =[(# of rows-1)(# of columns-1)] d.f. In this case, the degrees of freedom are equal to (2-1)*(2-1) = 1. The critical chi-square value from the table using P<0.10 is 2.706. The calculated chi-square value of 29.06 is greater than the critical value, so we reject the null hypothesis of no difference in amount of vehicle use. The rows (Tracked Vehicle Use) and the columns (Slope Steepness) are not independent of each other. Based on the sample data, we can conclude at a 90% level of confidence that tracked vehicle use is significantly higher on slopes <25% compared to slopes <25%. The p-value can be interpolated using the chi-square table of critical values.

Contingency tables and chi-square tests can be prepared for multiple samples and/or years. The procedures are the same as those used for the 2x2 contingency table. Interpretation of the Chi-square results follow those for interpreting ANOVA results: a rejection of the null hypothesis only indicates that at least one of the proportions is significantly different. The results do not indicate which sample proportion is different.

11.5.4.2 McNemar's Test

McNemar's test is applied to frequency data collected on permanent plots, where some independence is assumed between samples. As with chi-square applications, the data consists of frequency data where a quadrat or point is considered the sampling unit. The structure of the contingency table for the McNemar's test is identical to the setup for the chi-square test. McNemar's test cannot be used to compare more than two years of data (no more than 2x2 table). Table 48 contains sample frequency data for Species X, which was sampled using 116 permanently-located frequency frames in both 1997 and 1999. Results of chi-square and McNemar's test are presented in Table 49. For the equation for calculating the McNemar statistic, see Zar (1996).

Table 48. Contingency table or cross-tabulation table for McNemar's test.

	1997	1999	totals
present	73	64	137
absent	43	52	95
totals	116	116	232

Table 49. Chi-square and McNemar's test statistics and probabilities.

Test statistic	Value	df	Prob
Pearson Chi-square	1.444	1.000	0.230
McNemar Chi-square	3.528	1.000	0.060

The calculated P value is less than the threshold P value of 0.10. Therefore, we reject the null hypothesis that the proportions are the same for 1997 and 1999; the frequency of species X is significantly lower in 1999. If the same data were produced using temporary quadrats and the chi-square statistic were calculated, a significant difference would not have been found (accept H_a, P value = 0.23>0.10). A threshold p value of 0.05 would have resulted in our **not** rejecting the null hypothesis.

11.5.4.3 Wilcoxon Signed Rank Test

This test is used when there is a presumed underlying continuity in the data. The null hypothesis is: *There is no difference in the frequency distribution of plant litter between the spring and fall data collection periods* (Table 50). α= 0.05. There are 10 samples when the pair with a difference of zero is dropped. If more than 20% of the observations are dropped, this procedure is not an appropriate test.

Table 50. Plant litter cover estimated during spring and fall collections.

Plot Number	Spring	Fall	Difference	Rank
1	54	17	37	6
2	52	19	33	4
3	61	22	39	8
4	82	22	60	10
5	87	32	55	9
6	71	33	38	7
7	71	37	34	5
8	65	42	23	1
9	19	44	-25	-2
10	54	54	--	--
11	27	58	-31	-3
				$T = \|5\|$

The difference per plot is determined and all samples are ranked by the absolute value of the difference. Once ranked, the number of negative and positive samples is determined (in this example 8 of the samples are positive and 2 are negative). The values for the less frequent sign (negative) are summed ($-2 + -3 = |5|$). This is *T*.

Using a Wilcoxon Signed Rank Test table, $T_{\alpha(n=10)} = 8$ (two-sided test); therefore, $P<0.05$ and the null hypothesis is rejected. In other words, for 10 pairs a rank sum ≤ 8 is required to reject the null hypothesis at 5%. Because 5 is less than 8, the null hypothesis is rejected; *There is no difference in the frequency distribution of litter between the spring and fall data collection periods*. Based on the Wilcoxon Signed Rank Test for 10 pairs and an $\alpha = 0.05$, we can conclude that there is a difference in the frequency distribution of litter between the two seasons.

11.5.5 Multivariate Analyses

Multivariate Analysis encompasses a variety of statistical techniques that allow a user to examine multiple variables using a single technique. For example, whereas traditional univariate comparison techniques like t-tests and the chi-square test can be very powerful, one can only interpret the results based on the analysis of one manipulation variable. Multivariate techniques allow for the examination of many variables at once.

There are many different types of multivariate techniques that can be applied to vegetation analysis. It has traditionally been used by researchers and managers to identify plant communities, define successional trends, or pick out unusual plant assemblages as well as other uses. Several techniques have been developed specifically with vegetation analysis in mind. These include Detrended Correspondence Analysis (DCA) (Hill and Gauch 1980), Canonical Correspondence Analysis (CANOCO) (ter Braak 1987), and TWINSPAN (Hill 1979). Other techniques that were developed for applications other than natural resource management are Principal Component Analysis (PCA) (SAS Institute 1996), Cluster Analysis(CA) (SAS Institute 1996), and various other discriminate analysis techniques. PCA and CA will be examined in this section because they are effective tools which are supported by affordable statistical software packages.

Multivariate techniques can be very powerful, but their results must be interpreted with care. Some techniques are sensitive to particular data types and require that data be distributed normally. Others cannot be used with non-linear (e.g. classification) variables. Sometimes the techniques only identify trends, without statistical assurances regarding the confidence of the results. When using multivariate techniques, it is important to understand their respective intended uses, strengths, and limitations.

For discussions of ordination and multivariate techniques, see Ludwig and Reynolds (1988), Mueller-Dombois (1974), and Jongman *et al.* (1987). Information, references, and internet links are provided by "The Ordination Web Page" at http://www.okstate.edu/artsci/botany/ordinate/.

11.5.5.1 Principal Component Analysis (PCA)

PCA is used to examine relationships among several quantitative variables. The technique is particularly good at detecting linear relationships between plots of varying species composition, density, and cover (SAS Institute 1996). For Example, plots of principal components are an excellent way to conduct preliminary analysis of a vegetation classification scheme, in preparation for developing a vegetation map for an installation.

Principal components are computed as linear combinations of the variables used in the analysis, with the coefficients equal to the eigenvectors of the correlation or covariance matrix. The eigenvectors are customarily taken with unit length. The principal components are sorted by descending order of the eigenvalues, which are equal to the variances of the components.

When applied correctly, PCA is powerful for preliminary analysis of vegetation datasets, especially for analysis of plant community data. It is particularly effective as a means for clustering survey plots of similar composition, density, or cover. Univariate techniques such as analysis of variance (ANOVA) can subsequently be used to compare the principal components of the ordination.

11.5.5.1.1 PCA Example

The goal of this analysis is to examine whether the plant community definitions we've applied to the belt transect plots are reasonable and appropriate for these plots, by examining the similarities and dissimilarities of the plots.

The results of a Principal Components Analysis of woody species cover for 208 transects from a southeastern U.S. installation is presented in Figure 133. Raw data format is presented in Table 51. The plots were classified according to vegetation map categories to facilitate visualization of results.

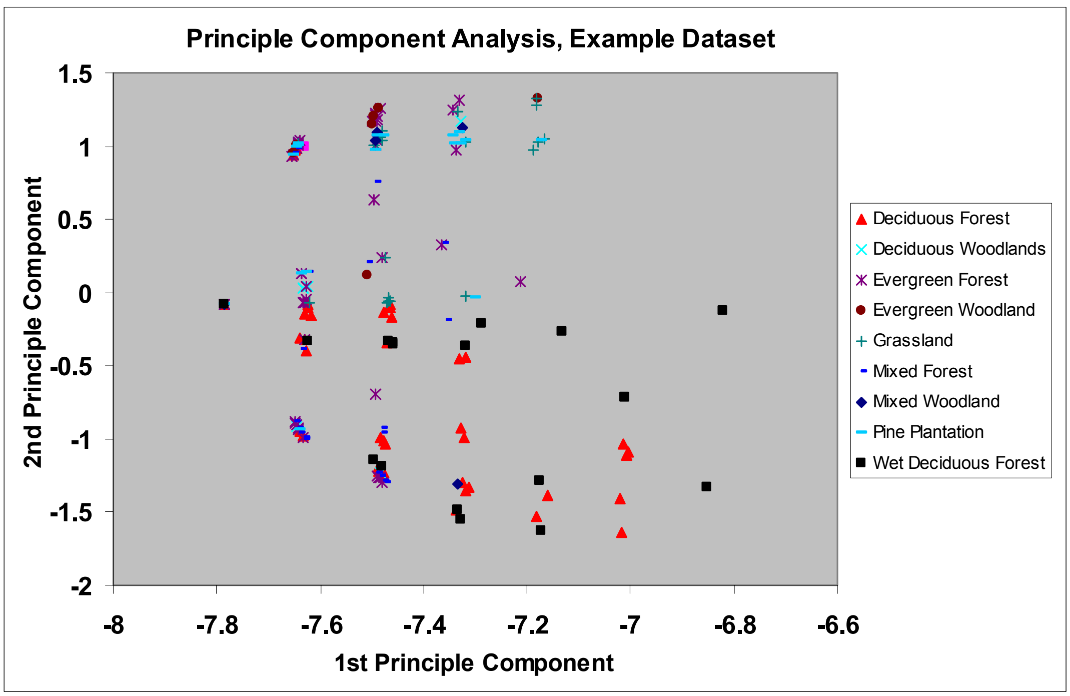


Figure 133. Principal Component Analysis of woody species densities from LCTA plots on a Southeastern U.S. Military Base. The X and Y axis variables are unitless.

Table 51. Subset of the data used in the principal component analysis and the cluster analysis example. Values shown are cover % of plant species (shown in columns) for each plot.

Plot	ACNE2	ACRU	ACSAF	AEPA	ALSE2	AMAR3	…
1	0	0	4	0	0	0	…
2	0	0	0	0	0	0	…
3	0	44	0	0	18	0	…
4	0	12	0	0	1	0	…
5	0	0	0	0	0	0	…
6	0	1	3	0	0	1	…
7	0	0	0	0	0	0	…
8	0	0	4	0	0	1	…
9	0	0	0	0	0	0	…
10	0	2	0	0	0	0	…
11	…	…	…	…	…	…	…

The PCA yields n-1 principal components for n variables in an analysis. The first two principal components provide the most information, in this case accounting for over 96% of the variance in the model. For this example we used canopy cover of all plant species with at least 10% cover. For analyses of this type, uncommon taxa do not contribute substantially to vegetation classification analysis since their effects are masked by the most abundant taxa. This is not to say that uncommon taxa should not be evaluated using PCA. To do so, one should structure the dataset to include the taxa of interest, and eliminate from the dataset the dominant taxa that may mask the effects of the uncommon taxa on the ordination.

A visual examination of Figure 133 indicates that points for deciduous forest and wet deciduous forest occupy the same space in the ordination. Mixed Forest types are clustered toward the left, and grasslands and pine plantations tend toward the top. There is, however, substantial visual overlap between the groupings, which suggests that shrub and understory species may be contributing significantly to the ordination model.

Analysis of variance of the principal components based on the preliminary vegetation classification indicates that most of the groups have a statistical basis for the groupings assigned by the field crews. The analysis also points out, however, that there is substantial variation within the Pine Plantation classification, suggesting that other factors other than the reforestation management regime may be a factor in defining the dominant vegetation in the plots.

The ordination of the pine plantation data suggests that a single classification may not be appropriate for those plots. Running a PCA ordination on just the Pine Plantation data yields the ordination shown in Figure 134. Note that the locations for the points on this diagram are quite different from those in Figure 133. It is important to note also that results of an ordination will vary greatly depending upon the contents of the dataset. The resulting ordination will place plot points in very different points in ordinal space depending on whether the data contains plots from a single vegetation classification type or several different classification types.

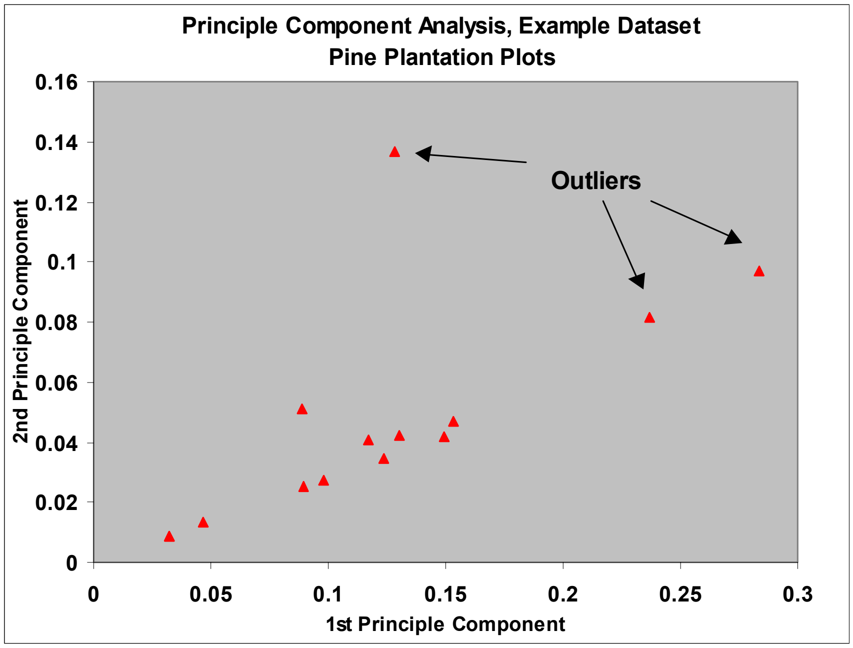


Figure 134. Principal Component Analysis of plant cover from Pine Plantation monitoring plots on a Southeastern U.S. Military Base. The X and Y axis variables are unitless.

An analysis of variance of the principal components indicates that the three points in the upper right corner of the diagram are outliers. This suggests that these three plots may have vegetation characteristics that distinguish them in some way from the other plots. At this point it seems appropriate to examine the dominant vegetation in these plots and determine what the source of the variation may be.

11.5.5.2 Cluster Analysis

Cluster analysis hierarchically clusters observations or samples based on the coordinates of the observations. That is to say, it uses separating algorithms to analyze the differences and similarities of a group of points in a two-dimensional space, and then separates the points in a hypothetical set of clusters based on their locations in the x-y plane and their relative distances from one another.

In order to utilize cluster analysis, one must first use some type of ordination technique to produce coordinates in ordinal (x, y) space that represent the various observations in your dataset, and then use cluster analysis to define the various clusters that may be present. The PCA example used in section 11.5.5.1.1 is just one type of ordination technique that can be used prior in cluster analysis. For this example we will use the SAS CANDISC procedure, which is a form of canonical discriminate analysis (SAS 1996).

11.5.5.2.1 Cluster Analysis Example

The first step after conducting the ordination is to determine the hypothetical number of clusters that the ordination has produced. Field crews identified nine different forest types, so it makes sense to ask the cluster analysis algorithm to attempt to divide the data into nine clusters. The first example of this, however, produces chaos on the ordination diagram. Figure 135 shows the results of the analysis, without the clusters assigned. One can see that it is difficult to imagine nine different clusters of points in the analysis, and Analysis of variance of the coordinates of the clusters indicates that there is no statistical basis for producing nine different clusters. Careful inspection of the ordination diagram indicates, however, that there appear to be three relatively obvious clusters of data points.

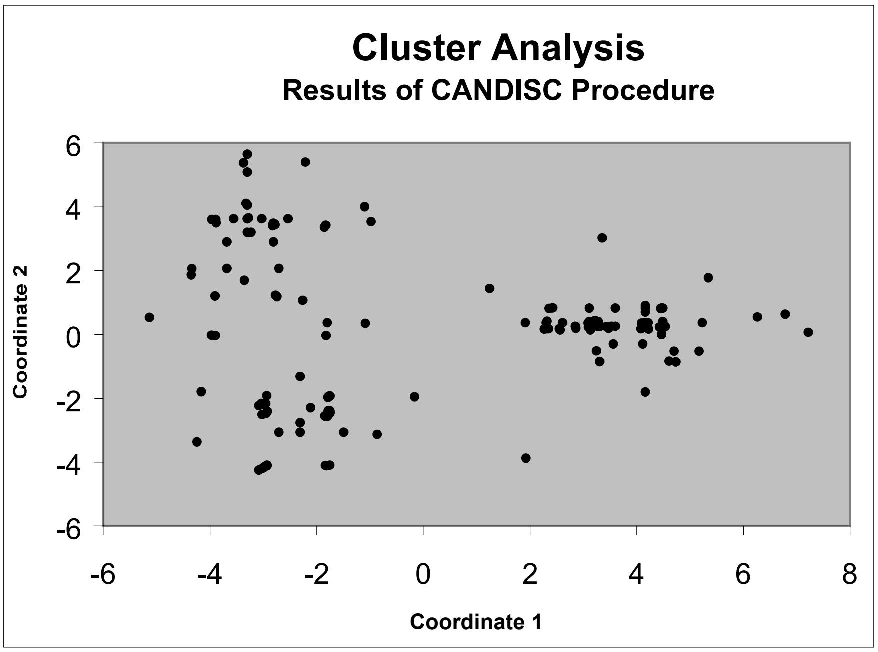


Figure 135 . Ordination diagram of the example dataset, showing x-y positions of the 208 LCTA plots based on the first two coordinates produced by the ordination.

Specifying that only 3 clusters be produced in the cluster analysis produces the ordination diagram shown in Figure 136 . Analysis of variance of the x and y coordinates establishes that there is a statistical basis at the .05 level for separating the LCTA plots into three clusters.

Table 52 shows how the relative proportions of the vegetation types are separated by the three clusters. A subjective analysis of the forest types indicates that the analysis tends to cluster coniferous forest/ woodland types toward the bottom of the diagram and deciduous types toward the top. There are numerous other factors that appear to be involved, however, as there are exceptions to this trend. Whereas pine plantation plots are placed in clusters 2-3-1 (in order of importance), evergreen forest plots are placed in clusters 1-2-3 and evergreen woodland plots are placed in clusters 2-1-3.

Discussions with the field crews and the installation forester indicate that seeded pine plantations are frequently located according to their proximity to roads within the installation. In many cases pine plantations were started in areas that were previously cleared of deciduous vegetation or previously were grasslands, and the dominant understory vegetation persists throughout the stands. The vegetation classification is based primarily upon the dominant vegetation within the plots. The dataset used for this analysis includes the several dozen smaller shrub, herb, and graminoid species in addition to the tree or large shrub overstory species. Hence, one may conclude that the vegetation classification system used should be expanded to include dominant understory vegetation as well as overstory species. It might be prudent to examine other edaphic factors at the plots, such as soil type, slope, aspect, and relative age of the forest in defining the dominant vegetation classification.

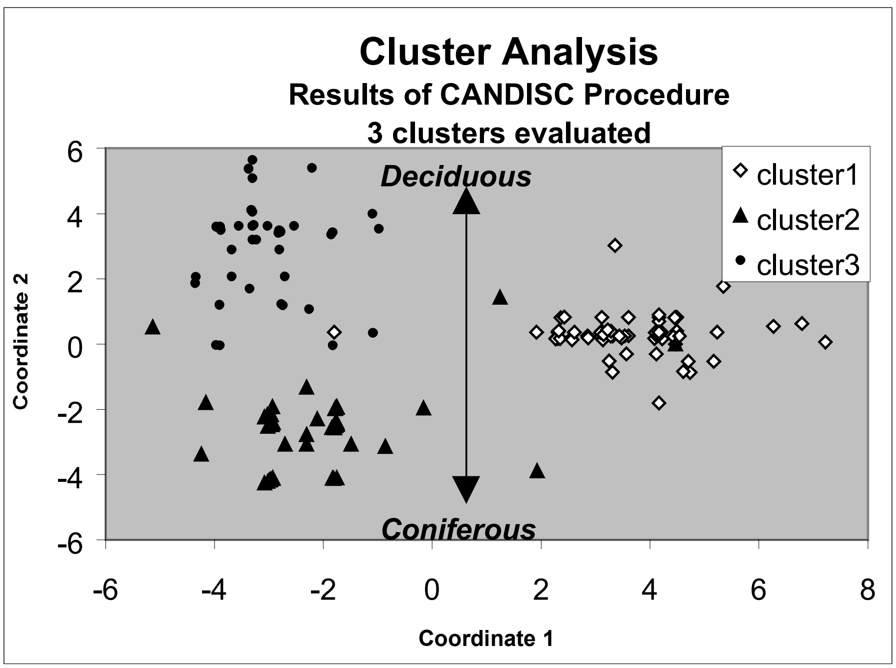


Figure 136. Results of the cluster analysis with three hypothetical clusters specified.

Table 52 . Results of the Cluster Analysis. The relative percentage of the number of plots by vegetation type are shown.

	Forest Types*							
Cluster	**DF**	**DW**	**EF**	**EW**	**GR**	**MF**	**PP**	**WDF**
1	12.21	2.33	11.63	1.16	3.49	3.49	0.58	3.49
2	1.16	1.74	9.3	2.33	4.07	7.56	8.14	0
3	9.88	0.58	2.91	0.58	0	4.07	2.33	5.23

*DF = deciduous woodland DW = deciduous woodland EF = evergreen forest EW = evergreen woodland GR = grassland MF = mixed forest PP = pine plantation WDF = wet deciduous forest

11.5.5.3 Summary

This section described various analysis tools and demonstrated applications to monitoring data. Natural resource managers are rarely limited in the type of analyses they can use. Whereas the statistics mantra "the experimental design determines the type of statistical analysis" is very often true, it does not restrict the analyst to conducting other types of analyses that he or she determines to be prudent.

Whereas the above examples were based upon cover, a measured variables, other variables such as stem density or biomass estimates could be used. Ordination can also be done on soil classification data, soil loss estimates, or combinations of these types of data. Ordination is useful for combining a large number of variables and using them to uncover trends or patterns that are otherwise not evident.

Ordination techniques described are very powerful, but the results can be misleading if misapplied. It is imperative that the resource manager become familiar with the techniques and apply them as carefully as possible to the resource management questions that he or she is investigating.

11.5.5.4 Multivariate Analysis Selected Bibliography

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11.6 Interpreting Results

The interpretation of monitoring results analyzed using confidence intervals is discussed in section 11.3. Based on results, the interpretation can be made that a threshold is crossed/met, when dealing with threshold objectives, or that the threshold or target was not met/crossed. Interpretation of confidence intervals or limits is straightforward and the results are easy to communicate with a variety of audiences. However, just because a threshold falls within the confidence interval for a sample mean, there is still some possibility that the sample mean is either below or above the true population mean, since the true population mean may fall anywhere within the confidence interval, at the specified level of confidence.

Interpreting the results of statistical tests is superficially straightforward. However, interpretation goes beyond simply stating the decision rule associated with the null hypothesis, especially when the monitoring objective involves change detection. A decision key to interpreting quantitative monitoring results is presented in Figure 137.

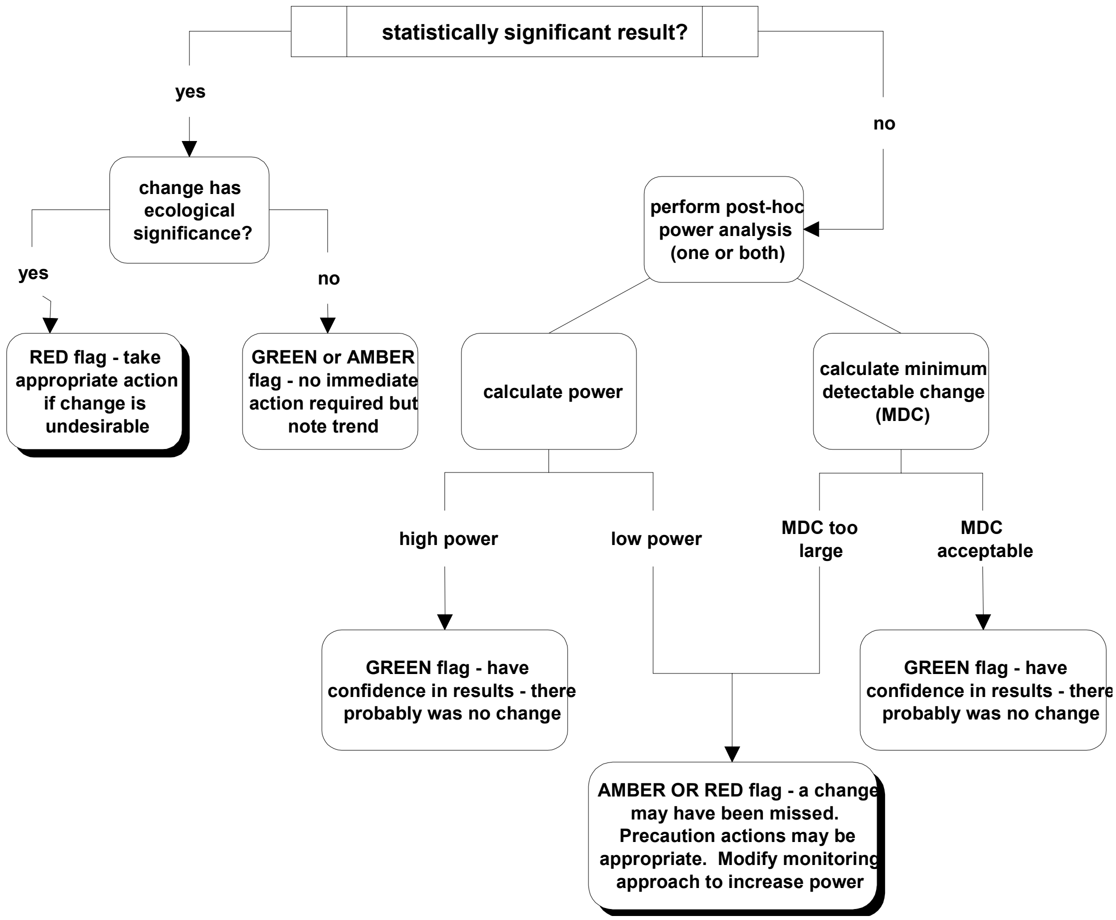


Figure 137. Interpreting the results from a statistical test examining change over time (adapted from The Nature Conservancy 1997).

Interpretation of results will depend on what constitutes an ecologically significant change in the resource of interest and the statistical power or minimum detectable effect size (MDC) associated with the sample data. In most cases, given the cost of monitoring, the MDC specified in the monitoring objective should probably not be smaller than one that is biologically significant. Natural variability plays a role in determining the minimum detectable effect size. For example, if number of oak seedlings varies on average by 25% from year to year, then specifying a relative minimum detectable change of 10% may result in a costly sampling program that detects a significant change (10%) that is not ecologically significant. In the case of the oak seedlings, specifying a relative MDC of 50% might be more realistically achieved at significantly reduced cost.

Statistical power or MDC size can be calculated using post-hoc power analysis. If the statistical test of differences between time periods shows no statistical difference, it may be that a change has in fact occurred but that the design used had low statistical power, which translates into the ability to only detect a relatively large change. Therefore, before you conclude that the null hypothesis is true (no change took place), determine the power of the test. Perhaps the sample sizes were too small , or the background variation too large, to determine any but the largest differences between treatments or samples. A nonsignificant but obvious trend suggests that the null hypothesis should not be accepted, but it cannot be rejected either (Fowler 1990). Examples and discussion of post-hoc power analysis and minimum detectable change calculation are provided in section 3.1.6 (Hypothesis Testing and Power Analysis).

11.7 Climate Data Summarization

11.7.1 Sources of Climatic Data

Climatic data is available from a number of sources. They include published records available through libraries, national weather service data, private sources which provide a wide range of regional or global climatic data, state or county agencies or services, local airports and airfields, or collection by the installation itself using meteorological equipment or stations. Extensive meteorological data, including current conditions and long-term summaries, are available from a number of sources at no cost on the World Wide Web. The principal variables of interest include precipitation, temperature, wind direction and speed, evaporation rates, and relative humidity. In some geographic regions, seasonal and yearly variations in climate greatly influence the response and growth of vegetation. In these cases, and where sampling designs permit, tools such as analysis of covariance may be helpful in accounting for variability due to climate vs. variability due to other factors.

11.7.2 Probability of Weekly Precipitation and Climate Diagrams

Historical data can be used to predict the likelihood of climatic and soil moisture conditions during the course of the year. If training exercises, especially those involving mechanized vehicles, are scheduled during periods where the likelihood of wet soils is high, then vegetation loss, soil compaction, and erosion losses are likely to be relatively high compared to periods of drier soils. In general, damage to soil and vegetation associated with training activities is minimized during periods of dry and frozen soils compared to moist or wet soils. Several graphic tools have been developed to help understand seasonal patterns of precipitation and soil moisture: 1) probability of weekly precipitation graphs, and 2) climatic diagrams developed by Walter (1985) and modified for applications in military land management (Tazik et al. 1990). Probability of weekly precipitation graphs and climatic diagrams are discussed and examples are presented in Tazik et al. 1990.

11.7.2.1 Probability of Weekly Precipitation

The probability of weekly precipitation is defined as the likelihood of receiving more than a given amount of total precipitation during a specified 1-week period. Probabilities are typically based on long-term records (25-30 years of data). A moving average can be used to smooth weekly values by using the mean of the previous, current, and following weekly values for the current value. From a military training standpoint, probability of weekly precipitation uses include planning of water crossings on intermittent streams, testing equipment under wet or dry conditions, and minimizing the need for rescheduling range activities, weapons instruction, and equipment use. In terms of land management, the probability graphs are useful to identify optimum periods for seeding, tree and shrub planting, and acquiring cloud-free satellite imagery (Tazik et al. 1990). A calendar of 1-week periods and exemplary weekly data is presented in Table 53. Weekly probability data is presented in graphic form in Figure 138. Data may also be presented using line graphs, with each line representing a specified minimum precipitation threshold. For the location represented in Figure 138, the probability of precipitation is generally high. Precipitation probabilities are lowest in October (weeks 40-43). Precipitation generally peaks during March, July-August, and December. Seasonal patterns of precipitation are highly influenced by geographic location and local or regional physiography, and are therefore more pronounced in some locations relative to others.

11.7.2.2 Climate Diagrams

Because soil moisture is greatly influenced by both the amount of precipitation received and temperature, which greatly influences evaporation and transpiration, integrating the two variables provides a useful management tool. The purpose of the modified Walter climate diagram is to : 1) synthesize temperature and precipitation in order to represent soil moisture conditions, 2) illustrate the approximate length of the growing season and period of frozen soils, and 3) characterize average monthly precipitation and temperature. Use of the diagram can enhance land management efforts by identifying periods where the risk of damage to vegetation and soils is elevated.

An interpretive guide to the climate diagram is presented in Figure 139. The diagram is constructed by plotting both average monthly temperature (°C) and average monthly total precipitation (millimeters) on an year-long time scale in months. Temperature and precipitation are scaled at 1 °C = 2 mm of precipitation. Where the temperature curve is above the precipitation curve, conditions are increasingly arid. Where the temperature curve is below the precipitation curve, conditions are more humid. Soil moisture should reflect these predominant climatic conditions. In cold climates, several lines are added to the diagram to enhance utility to the training and land management community (Figure 140). One line is placed across the diagram at 10 °C. The period where the temperature exceeds 10 °C is generally considered the growing season, assuming soil moisture is available. The second line, representing the point of freezing for soils, is drawn at 0 °C. If soil moisture is present, soils will freeze at or below this temperature. During periods of frozen soils, off-road maneuvers (including both mechanized and motorized vehicles) have minimal impacts to soil structure. Additional examples of climatic diagrams for locations in the southeastern and northwestern U.S. are presented in Figure 141 and Figure 142. Where a significant proportion of winter precipitation is received as snow, soils may be wetter than indicated by the diagram during periods of snowmelt.

Graphic and or statistical examination of climatic data is also useful in understanding interannual variability, especially in arid climates, where yearly fluctuations in temperature and precipitation or patterns thereof can have significant ecological responses. Figure 143 illustrates year to year variability in temperature and rainfall patterns relative to the long-term averages. It is evident that while temperatures for all years approximated the long-term mean, patterns of precipitation varied widely in some years. Spatial variability of climatic variables is also considerable where localized events or physiographic effects result in large variations in climate within the same installation. For example, Figure 144 contains precipitation data collected from seven weather stations within a watershed on a Great Basin installation. Even though total annual precipitation may be the same for different locations, the temporal distribution can differ significantly.

Table 53. Example of format of weekly climatic data used to construct long-term averages and calculate probabilities of weekly precipitation.

YEAR	WEEK	DATES	PRECIP (mm)	AVG MAX (deg. C)	AVG MIN (deg. C)	AVG MEAN (deg. C)
1965	1	JAN 1-7	5.1	19	5	12
1965	2	JAN 8-14	10.2	12	1	7
1965	3	JAN 15-21	27.9	15	-1	7
1965	4	JAN 22-28	11.4	17	1	9
1965	5	JAN 29-FEB 4	37.8	11	-2	4
1965	6	FEB 5-11	24.4	22	11	17
1965	7	FEB 12-18	78.5	13	2	7
1965	8	FEB 19-25	8.9	15	0	7
1965	9	FEB 26-MAR 4	30.2	15	4	10
1965	10	MAR 5-11	54.1	12	2	7
1965	11	MAR 12-18	23.9	20	7	13
1965	12	MAR 19-25	29.0	22	9	15
1965	13	MAR 26-APR 1	3.0	22	11	17
1965	14	APR 2-8	2.8	27	15	21
1965	15	APR 9-15	1.8	26	12	19
1965	16	APR 16-22	2.0	27	13	20
1965	17	APR 23-29	0.5	26	12	19
1965	18	APR 30-MAY 6	0.0	30	11	21
1965	19	MAY 7-13	0.0	32	15	23
1965	20	MAY 14-20	19.1	32	17	24
1965	21	MAY 21-27	25.9	32	19	26
1965	22	MAY 28-JUN 3	46.7	31	18	24
1965	23	JUN 4-10	25.1	29	21	24
1965	24	JUN 11-17	17.8	28	20	24
1965	25	JUN 18-24	5.6	30	18	24
1965	26	JUN 25-JUL 1	2.3	32	21	27
1965	27	JUL 2-8	74.9	31	21	26
1965	28	JUL 9-15	5.8	30	22	26
1965	29	JUL 16-22	8.6	32	21	26
1965	30	JUL 23-29	62.2	31	22	27
1965	31	JUL 30-AUG 5	52.1	31	20	25
1965	32	AUG 6-12	63.5	30	21	25
1965	33	AUG 13-19	5.6	32	22	27
1965	34	AUG 20-26	4.1	33	21	27
1965	35	AUG 27-SEP 2	28.2	30	20	25
1965	36	SEP 3-9	6.1	30	19	24
1965	37	SEP 10-16	0.0	32	21	26
1965	38	SEP 17-23	2.5	30	19	24
1965	39	SEP 24-30	48.5	25	19	22
1965	40	OCT 1-7	31.8	24	14	19
1965	41	OCT 8-14	1.3	27	13	20
1965	42	OCT 15-21	0.3	22	14	18
1965	43	OCT 22-28	0.0	20	3	12
1965	44	OCT 29-NOV 4	0.0	24	8	16
1965	45	NOV 5-11	17.8	22	10	16
1965	46	NOV 12-18	0.0	20	7	13
1965	47	NOV 19-25	23.9	21	9	14
1965	48	NOV 26-DEC 2	0.0	14	0	7
1965	49	DEC 3-9	0.0	18	-2	8
1965	50	DEC 10-16	42.7	15	9	12
1965	51	DEC 17-23	26.2	16	1	8
1965	52	DEC 24-21	0.0	19	3	11

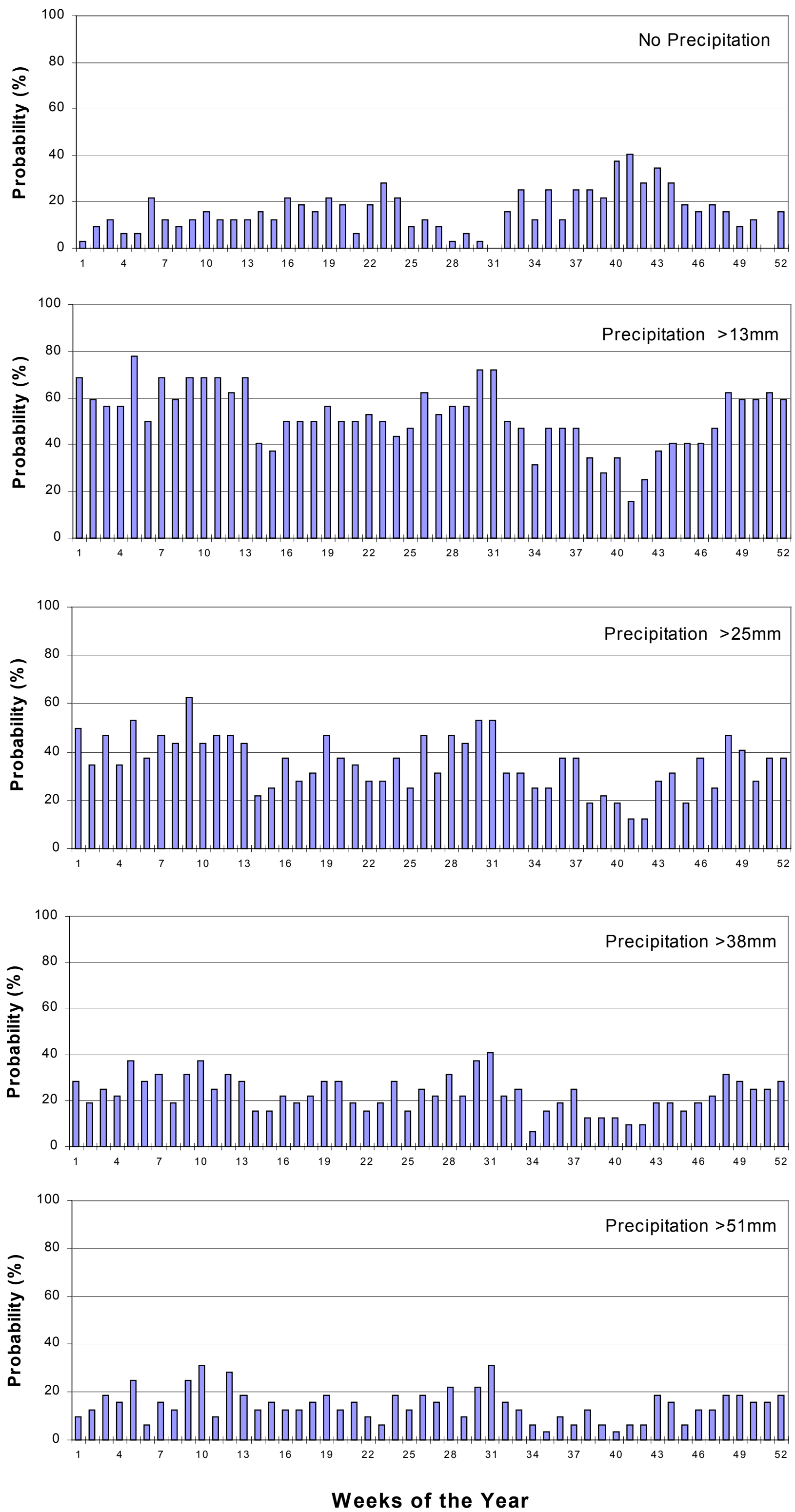


Figure 138. Probability of weekly precipitation of 0 mm (no precipitation), greater than 13 mm, greater than 25 mm, greater than 38 mm, and greater than 51 mm. Data is from a southeastern Army installation.

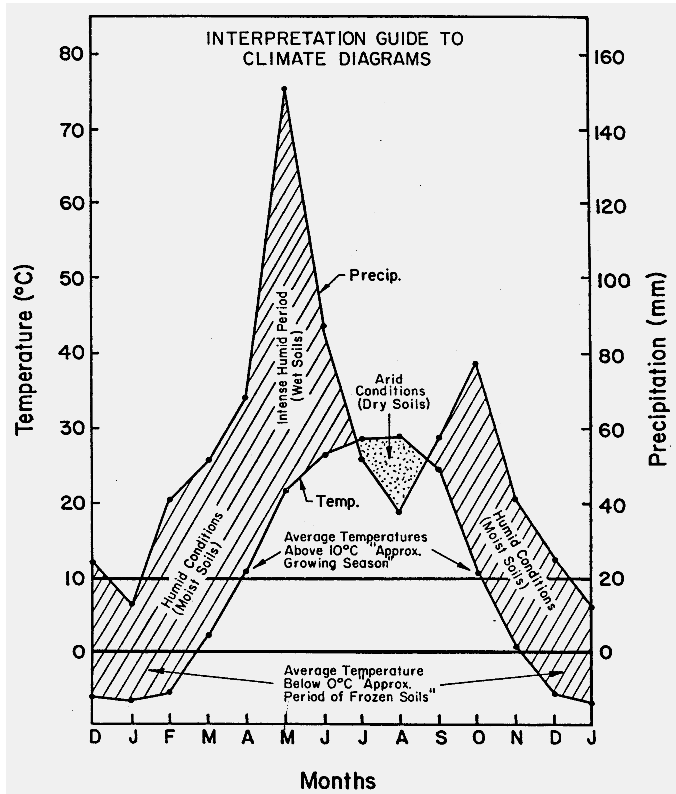


Figure 139. Interpretation guide to modified Walter climate diagrams. Reprinted from Tazik et al. 1990.

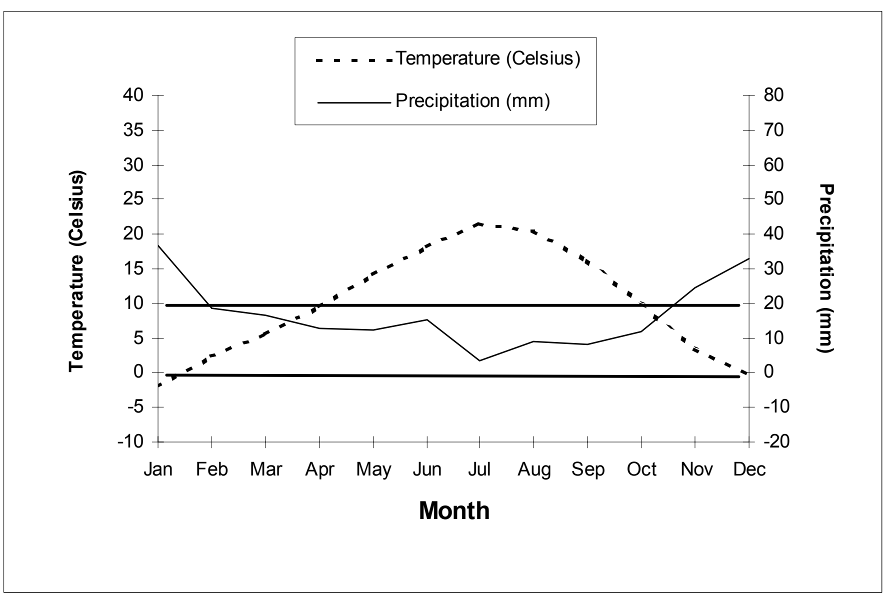


Figure 140. Climatic diagram for an installation in the Great Basin, based on long term (30 year) temperature and precipitation records.

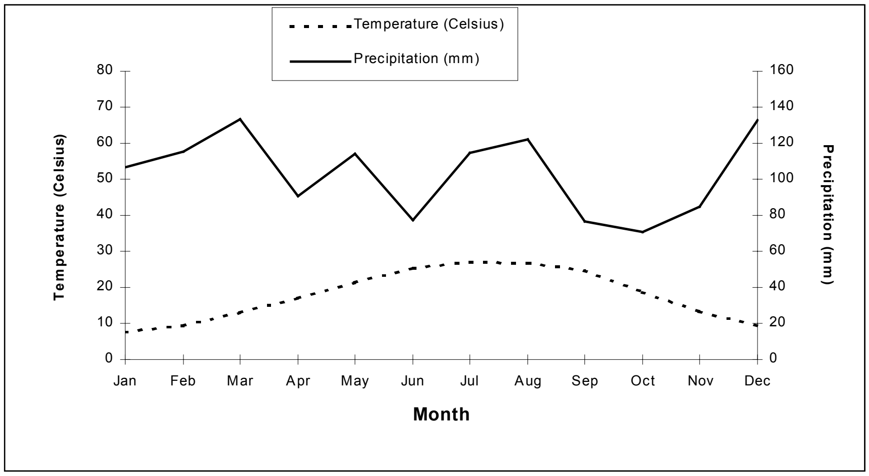


Figure 141. Climatic diagram for an installation in the southeastern United States, based on long term (30 year) temperature and precipitation records.

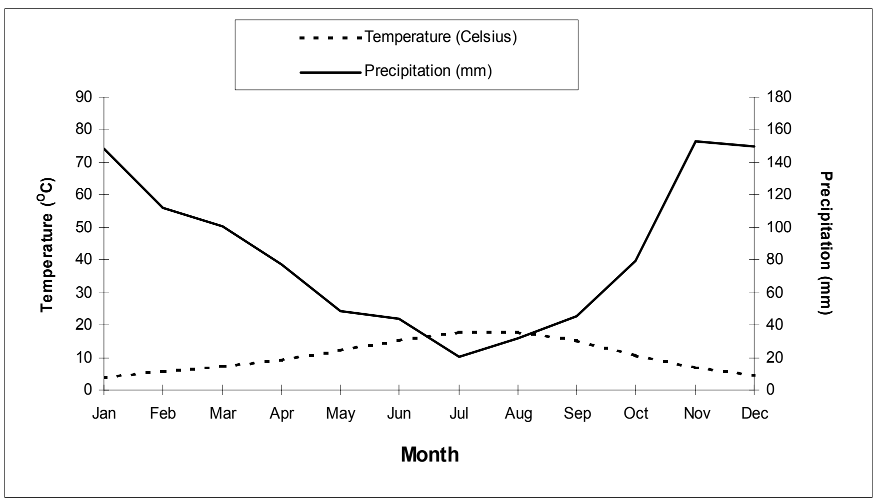


Figure 142. Climatic diagram for an installation in the northwestern United States, based on long-term temperature and precipitation records.

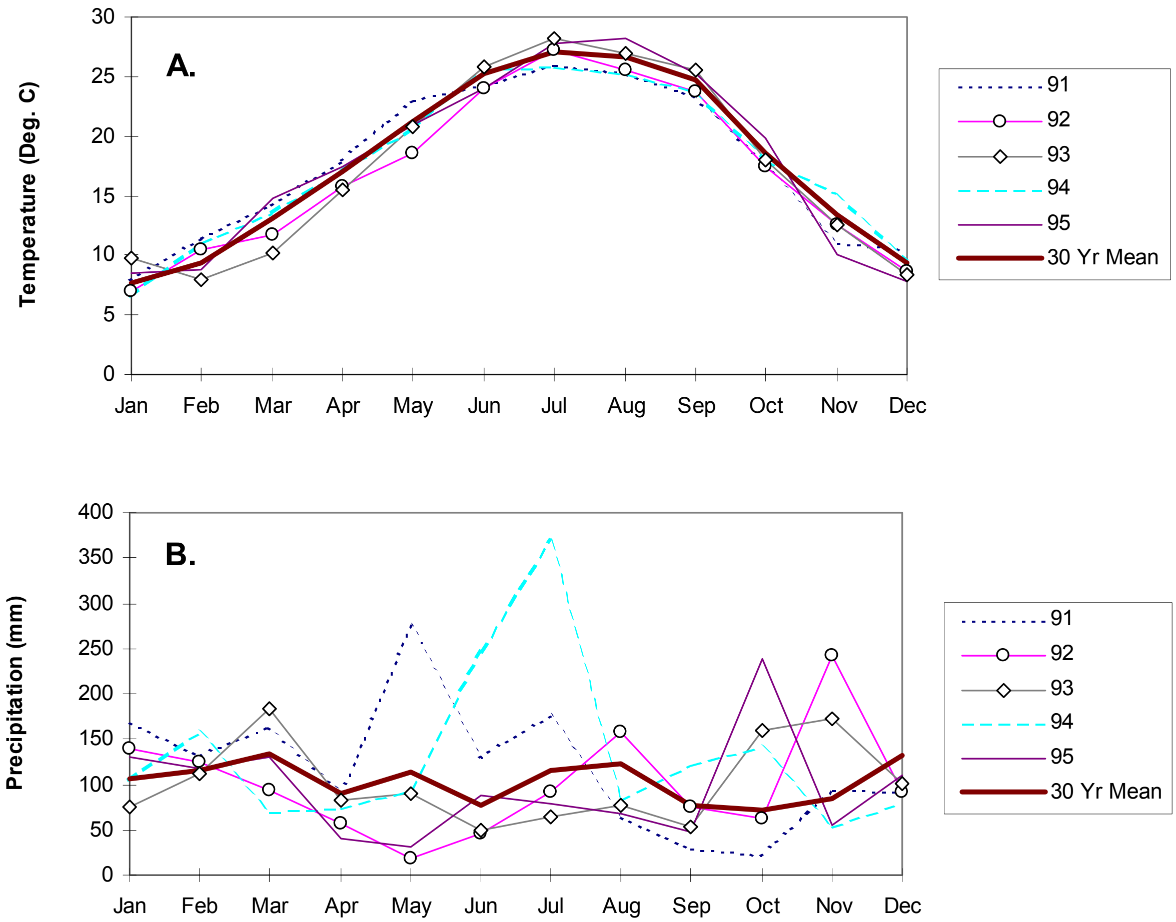


Figure 143. Monthly mean temperature (A) and precipitation (B) for a five year period compared to long-term averages (southeastern U.S.).

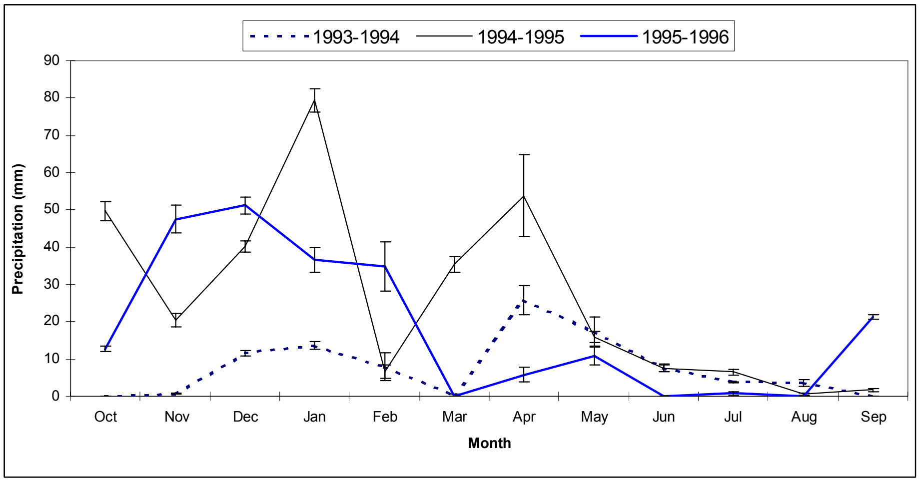


Figure 144. Means and standard errors for precipitation by month for seven weather stations within a large watershed (Great Basin data).

11.8 Extrapolating Results

Statistical extrapolation is the process of estimating or inferring beyond the known range based on a sample of known values. Making inferences about an administrative unit, and management unit, or an ecological unit requires that samples are collected and summarized according to certain principles. Sampling design and plot allocation determine the targets and limitations associated with sampling, and should guide the process of estimating parameters for the populations or communities represented. Sampling design and the concept of target populations is introduced in Chapter 3. Samples must be aggregated in order to make inferences about the population of interest. A minimum of 2 samples is required to generate a measure of variability for a sample mean. Considerably larger sample sizes are required to provide acceptable levels of precision .

The method of sample extrapolation is sometimes provided by the method of plot allocation. Simple random samples are in no way constrained – every possible location has an equal chance of receiving a sample. If any areas are excluded from the allocation, statistically speaking they are not represented by the sample. Simple random samples can be aggregated (i.e., grouped) using any variable. Allocation in proportion to area ensures that sampling intensities are equal within the specified geographic boundaries of the study area. Grouping variables that reduce heterogeneity are the most advantageous. Subjectively located plots, including macroplots, only represent the plot or area sampled; results cannot be extrapolated statistically beyond plot boundaries.

11.8.1 Grouping Data

Post-sampling stratification involves stratifying or grouping a sample after the data is collected (Snedecor and Cochrane 1980). Grouping the data by strata typically results in groups that are more homogeneous than the sample as a whole. Strata often used include vegetation types, soil types, and land-use types.

Stratified random sampling typically draws upon existing knowledge, information, or pilot data to delineate strata and assign a given sample size to each allocation category. In some cases the sample sizes are equal among strata, but most often the sample sizes are unequal. Because all samples are allocated randomly in a stratified random allocation, plot locations are by definition unbiased. For this reason, it is not uncommon to re-aggregate sample data into groups that are different from those used in the original allocation. In so doing, data analysis and examination is more flexible and may reveal patterns or differences that are not readily apparent using the initial stratification scheme. However, care must be taken to ensure that samples are both random and unbiased. For example, if a high proportion of samples is allocated in a small portion of the area of interest, then that area is represented by a larger proportion of samples than other areas or strata within the larger area of interest. In such a case, aggregating samples using a simple average mathematical function may result in bias because a large proportion of the samples represent a smaller area that may or may not be representative of the larger area of interest.

Some strata are well-suited to some types of analyses and poorly suited to others. For example, examining data using drainage or watershed boundaries is logical from the standpoint of hydrological response, soil erosion, and water quality. However, watershed boundaries may not be logical divisors of vegetation communities, soil types, or ecological communities (unless the divides consist of high mountain divides that present significant obstacles to species migration, as in the case of weed distribution and movement).

For example, data summaries are often requested using military training areas or other administrative boundaries used by the training community, and to some extent the natural resource management community. However, these boundaries are largely artificial in nature, often bearing no relationship to natural features of the landscape and sometimes represented by roads and arbitrary straight lines. For example, a large portion of most installation boundaries and impact areas are delineated using straight lines that often correspond to grid coordinates, county boundaries, or other artificial divisions. Using administrative boundaries as a grouping variable will likely result in high variability for the attributes examined.

The list of possible grouping variables for summary and analysis is similar to that used for stratified random plot allocation:

- military training areas or other administrative boundaries
- types of training activity/land use
- potential training type (maneuver, bivouac, dismounted only)
- vegetation type/plant community classification type
- ecological land classification
- land maintenance activity

- erosion evidence
- evidence of burning
- soil physical & chemical properties
- soil series
- erosion potential or current erosion status based on estimates
- aspect
- slope steepness
- presence of plants of concern
- rangesite (Western NRCS classification found in soil surveys)
- range condition (objective or subjective, qualitative or quantitative)
- watershed or subwatershed
- habitat or community type (from local, state, regional, heritage or other classification)
- landcover/soil type following original LCTA allocation methods (Tazik et al. 1992): integrates historic and current disturbance with potential vegetation
- historic land use
- elevation
- precipitation zone
- multivariate analysis (vegetation composition, site characteristics, soil chars, etc.) – post-hoc aggregation/grouping.

Care should be taken when using the sample data itself to create post-hoc strata or grouping categories. Remember that in most cases, plot allocation is done on a spatial basis. That is, samples are allocated to discrete areas that are identifiable and have meaning. If, for example, it is decided that all (randomly allocated) burned plots will be aggregated and that all unburned plots will be similarly aggregated, the results may be informative and descriptive, and variances will probably be reduced. However, if the burned and unburned areas cannot be represented by geographic boundaries (i.e., are not mapped), then the results can be extrapolated to burned and unburned areas only, and not to parcels delineated on a map.

11.9 Linking LCTA and Remote Sensing Data

Data for ground truthing remotely-sensed data is often required in many applications utilizing remotely-sensed data. Such applications include change detection, classification, and classification accuracy assessment. In many cases, monitoring (e.g., LCTA) data can be utilized as ground-truth data for classification or accuracy assessment.

11.9.1 Assess Land Condition and Trends

Monitoring data has the potential to be used to detect changes in resource condition (Senseman et al. 1995). Since monitoring information is often based on a random sample, it alone may be inadequate for detecting the locations and amount of change that occur across the landscape. This problem may be compounded by inadequate sample sizes . However, by using plot data and remotely-sensed data such as multi-spectral satellite imagery, it may be possible to identify and quantify change where no field data were collected through the geographic extrapolation of sample data.

A general approach for linking monitoring data with remotely-sensed data for land condition and trend analysis is to determine the relationship between the field data and the remotely-sensed data. Developing a vegetation index is a typical example (Senseman et al. 1996). In effect, the remotely-sensed data is used as an indirect means to document resource condition, thus permitting land condition analysis where no monitoring data were directly collected. By repeating this procedure in subsequent years, it is possible to determine if and where change (i.e. trends) has occurred.

11.9.2 Classify and Ground Truth Remotely-Sensed Images

Whether using aerial photography or multi-spectral satellite imagery, monitoring data provides an opportunity for ground truthing remotely-sensed data. Monitoring data can be used in landcover mapping and its subsequent accuracy assessment. Splitting the LCTA data into two data sets makes it possible to use the data for both applications. The same plot data cannot be used to both develop and assess a map because of the high correlation that would be expected at those points regardless of the overall quality of the map or classification.

Remotely-sensed data is often used to derive information related to landcover, such as a vegetation map. Multi-spectral satellite imagery is often used to map general landcover types. Plot and other monitoring data can be used in the supervised classification of this remotely-sensed data. In this type of application, the sample data would be used to “train” the supervised classification.

Accuracy assessment of vegetation maps is another potential application. A vegetation map may be derived from the processing of multi-spectral satellite imagery of from traditional aerial photography interpretation. In either case, LCTA or other site-based data can be used to calculate statistics for an accuracy assessment of the vegetation map. If a sufficient number of LCTA plots is available, then the data may be used as both training data for the supervised classification of satellite imagery and the subsequent accuracy assessment of the resultant map. The LCTA data must be split into two data sets for the dual use of the data. Accuracy assessment procedures are described in detail by Senseman et al. (1995).

An excellent general resource to application of remote-sensing is Bright et al. 1997. This document provides a comprehensive overview of remote sensing applications for land management.

11.9.3 Accuracy Assessment of Classified Vegetation and Imagery

It is very common for an installation to have a vegetation map produced from remotely sensed data. Applying an image classification algorithm to the sensed data identifies vegetation types. Often this map is used in plot allocation. For the information derived from this map to be useful in decision making, its accuracy must be assessed. One way to achieve this is perform a site-specific error analysis, which compares the remotely sensed data against a "true" map of the area, or reference map. A reference map can be derived from sample data of the area. The LCTA plots were allocated using a stratified random method, which is an appropriate sampling method for accuracy assessment.

11.9.3.1 Data Needs

The data necessary for the analysis consists of the plot number, vegetation type from remotely sensed data image classification, and the plant community as determined from field surveys or plant community classification of field data. Any valid plant community classification can be used.

An error matrix is then constructed using the data mentioned above. An error matrix is derived from a comparison of a reference map to the classified map. Calculated plant communities represent the reference map and form the columns. The classified data form the rows. The error matrix is shown in Table 54.

Table 54. Error matrix for classification and reference data.

	Reference Data				
Classified Data	Dense Woodland	Open Woodland	Grassland	Sparse/ Barren	Row Marginals
Dense Woodland	30	0	0	0	30
Open Woodland	3	27	0	0	30
Grassland	0	0	30	0	30
Sparse/Barren	0	0	0	20	20
Column Marginals	33	27	30	20	110

The row marginals in the error matrix are simply the sum of the row values and the column marginals are the sum of the column values. The row marginals represent the number of plots in each classified category. The values in each cell across a row represent the number of plots in the category that fall into the reference data category. For example, the open woodland classified category contains 30 plots, 3 of which were classified as dense woodland using the plant community classification. The remaining 27 plots were classified as open woodland.

11.9.3.2 *Determining Sample Adequacy for Accuracy Assessment*

The first step is to determine if there are a sufficient number of plots, reference points, for an overall accuracy assessment of the classification. It has been shown that a minimum sample size of 20 per class is required for 85 percent classification accuracy, while 30 observations per class are required for 90 percent accuracy (Senseman, et. al. 1995). Notice in the table above, there are sufficient samples for a 90 percent accuracy assessment for three of four categories. Because the sparse/barren category only contains 20 plots, an 85 percent classification accuracy is used. The equation below computes the ideal number of points to sample as reference points:

$$N = (4\ (p)\ (\tilde{q}))\ /\ E^2$$

where

N = total number points to be sampled
p = expected percent accuracy
$\tilde{q}$ = 100 - p
E = allowable error.

For this example:

$$N = (4\ (85)\ (15))/\ 7.5^2 = 90.667 = 91 \text{ samples}$$

The example in Table 54 has 110 total plots, which is sufficient for an overall accuracy assessment.

11.9.3.3 *Percentage of Pixels Correctly Classified*

This is one of the most commonly used measures of agreement and is easy to calculate. Simply divide the number of points correctly classified by the total number of reference pixels. The equation is shown below.

$$\frac{\sum_{i=1}^{r} x_{ii}}{\sum_{i=1}^{r} x_{i+}}$$

The numerator represents the number of points correctly classified. This value is calculated by summing the diagonal entries from the error matrix. The diagonal values, from upper left to bottom right represent the number of points correctly identified in the classified image as compared to the reference data, calculated plant community. The denominator is the total number of reference pixels. This is the sum of the row marginals or the total number of points.

From the error matrix above:

(30 + 27 + 30 + 20) / 110 = .972727 or 97.3 % of the points were correctly classified.

It is also possible to determine if the percent of correctly classified points exceeds a pre-determined minimum classification accuracy. See Senseman, et. al. (1995) for further information.

11.9.3.4 Errors of Omission

Errors of omission refer to points in the reference map that were classified as something other than their "known" or "accepted" category value. In other words, points of a known category were excluded from that category due to classification error.

Errors of omission for each category are computed by dividing the sum of the incorrectly classified pixels in the non-diagonal entries of that category column by the total number of pixels in that category according to the reference map (i.e., the column marginal or column total). The values in the non-diagonal cells represent points that were classified differently in the reference map compared to the classified map.

Look down the column of values for dense woodland (Table 54). Notice the value 3 in the second row under this column. This number represents the number of plots classified as dense woodland, using the plant community classification, that were classified as open woodland on the classified image. The cells in the third and forth rows contain zero. The sum of incorrectly classified points is therefore 3. The value 30 in the first row represents the number of correctly classified points. The error of omission for dense woodlands is computed as:

3 / 33 = .0909 or 9.1% error of omission.

The remaining values were calculated and are shown in Table 55.

11.9.3.5 Errors of Commission

Errors of commission refer to points in the classification map that were incorrectly classified and do not belong in the category in which they were assigned according to the classification. In other words, points in the classified image are included in categories in which they do not belong. Errors of commission are calculated by dividing the sum of incorrectly classified points in the non-diagonal entries of the category row by the total number of points in that category according to the classified map (i.e., the row marginal or row total).

Read across the row for open woodland. Notice the 3 under the first column. This number represents the number of plots classified as open woodland in the classified map that were classified as dense woodland using the plant community classification. The value in the second column represents the number of plots correctly classified and is not used here. The remaining values in the row are zero, making the sum of incorrectly classified plots 3. The error of commission for open woodland is computed as:

3 / 30 = .10 or 10 percent error of commission.

The remaining values were calculated and are shown in Table 55.

11.9.3.6 Kappa Coefficient of Agreement

The final measure of agreement discussed is the Kappa Coefficient of Agreement. The Kappa Coefficient provides a measure of how much better the classification performed in comparison to the probability of randomly assigning points to their correct categories. The equation for the Kappa Coefficient of Agreement is:

$$\widehat{k} = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}(x_{i+} * x_{i+})}{N^2 - \sum_{i=1}^{r}(x_{i+} * x_{+1})}$$

where:

r = the number of rows in the error matrix
x_{ii} = the number of observation in row i and column i
x_{i+} = the marginal totals of row i
x_{+i} = the marginal totals of column i
N = the total number of observations.

From the error matrix (Table 54), the Kappa Coefficient is calculated as:

$$\frac{(110 * 107) - ((33 * 33) + (27 * 27) + (30 * 30) + (20 * 20))}{12100 - ((33 * 30) + (27 * 30) + (30 * 30) + (20 * 20))} = .96133$$

It is also possible to calculate a measure of agreement for each class by using the Conditional Kappa Coefficient of Agreement. This is calculated as:

$$K_i = \frac{(N)(p_{ii}) - p_{i+}p_{+i}}{(N)(p_{i+}) - p_{i+}p_{+i}}$$

where:

K_i = Conditional Kappa Coefficient of Agreement for the ith category
N = the total number of observations
p_{ii} = the number of correct observations for the ith category
p_{i+} = the ith row marginal
p_{+i} = the ith column marginal.

The Conditional Kappa Coefficient of Agreement for open woodland is:

$$\frac{(110)(27) - (27 * 30)}{(110)(30) - (27 * 30)} = .8674$$

Table 55. Summary table for accuracy assessment.

Category	**% Commission**	**% Omission**	**Conditional Kappa**
Dense Woodland	0	9.090909091	1
Open Woodland	10	0	0.86746988
Grassland	0	0	1
Sparse/Barren	0	0	1
Kappa Coefficient	0.96133333		
Observed Correct	**Total Observed**	**% Observed Correct**	
107	110	0.972727273	

By examining the measures of agreement in Table 55, it is concluded that the classification performed well. 97.27 percent of the plots, or 107 out of 110, were classified correctly. Looking at the values for each of the individual categories it can be stated that each performed well. The open woodland category was the only one that had plots incorrectly identified in the classification. Three of the open woodland plots were actually classified as dense woodland, using the plant community classification, resulting in a 10 percent error of commission. This means these plots were included in the classified category of open woodland when they do not belong there. Notice that the dense woodland category has a 9.09 percent error of omission. This suggests that three plots were classified as something other then their known or accepted category value. In other words, these plots were excluded from dense woodland due to a classification error.

Looking at the Conditional Kappa for each category it is concluded that all categories, with the exception of open woodland, were accurate. The open woodland was fairly accurate with a value of .8674. The remaining categories were classified exactly correct.

11.10 Additional Analyses

11.10.1 Biodiversity Indices

11.10.1.1 Diversity as a Management Concern

Biological diversity or biodiversity can be defined as the diversity of genes, species, communities, and ecosystems. Biodiversity is a simple general concept that rapidly becomes complex with attempts at measurement and comparison. Each level of biodiversity has three components: compositional diversity, structural diversity, and functional diversity. Compositional diversity is examined most often.

Considerable evidence suggests that biodiversity is being lost at a rapid rate. Most management approaches to minimize loss focus on species, often when an organism is nearing extinction. This species approach, however, can be inefficient and expensive, often focusing on symptoms rather than the underlying causes. Habitat management and protection is essential to species population stability and survival. Therefore, a successful management program should attempt to maintain an array of representative ecosystems. Also, both species and ecosystem-level approaches are necessary because ecosystem classification systems are often not comprehensive enough to encompass every species.

By examining the spatial and temporal distribution of different ecological communities, managers can evaluate the influence of management activities on community processes, species dispersal and migration (e.g., habitat linkages and migration corridors), or loss of habitat and artificial habitat fragmentation. For example, trends in herbaceous plant diversity can be examined following the introduction, cessation, or change in grazing regimes or burning prescriptions. Impacts to woody vegetation can be similarly examined following forest management activities. Additional examples of how diversity analyses can be applied and integrated with resource management include how neotropical migrant birds are affected by management activities over time and how land use activities adversely impact endangered species habitat. Structural diversity (e.g., foliar height diversity), a function of the number of vertical layers present and the abundance of vegetation within them, has been strongly linked to bird species diversity in woodland environments (MacArthur and MacArthur 1961). Caution should be exercised when inferring cause and effect from only several years of data. Long-term data may be required to reveal trends, especially in arid environments where year to year variability can be high.

11.10.1.2 Using Monitoring Data to Evaluate Diversity

The application of monitoring data and selection of a diversity statistic can be difficult because the measures of species richness, evenness, and diversity are themselves diverse and cannot be applied universally. Different installations may prefer different measures because of the distribution of habitats or relative abundance of species. The choice of statistic may also be influenced by the methods chosen by other land management agencies in the region in order to facilitate comparison of results.

Species diversity measures can be divided into three main categories. Species richness indices are a measure of the number of species in a defined sampling unit. Secondly, species abundance models describe the distribution of species abundance. The third group of indices (e.g. Shannon, Simpson) is based on the proportional abundance of species and integrates richness and evenness into a single number.

Table 56 summarizes the performance and characteristics of a range of diversity statistics showing relative merits and shortcomings. The column headed "Discriminant ability" refers to the ability to detect subtle differences between sites or samples. The column headed "Richness or evenness dominance" shows whether an index is biased towards species richness, evenness, or dominance (weighted toward abundance of commonest species). Those marked in bold are calculated by the Access LCTA program.

Table 56. Performance and characteristics of diversity statistics. Reprinted from Magurran (1988).

Diversity Statistic	Discriminant ability	Sensitivity to sample size	Richness or evenness dominance	Calculation	Widely used?
α (log series)	Good	Low	Richness	Simple	Yes
λ (log normal)	Good	Moderate	Richness	Complex	No
Q statistic	Good	Low	Richness	Complex	No
S (species richness)	Good	High	Richness	Simple	Yes
Margalef index	Good	High	Richness	Simple	No
Shannon index (H')	Moderate	Moderate	Richness	Intermediate	Yes
Brillouin index	Moderate	Moderate	Richness	Complex	No
McIntosh U index	Good	Moderate	Richness	Intermediate	No
Simpson index	Moderate	Low	Dominance	Intermediate	Yes
Berger-Parker index	Poor	Low	Dominance	Simple	No
Shannon evenness	Poor	Moderate	Evenness	Simple	No
Brillouin evenness	Poor	Moderate	Evenness	Complex	No
McIntosh D index	Poor	Moderate	Dominance	Simple	No

To calculate diversity statistics from LCTA plot data, plots should first be grouped by desired criteria. The chosen diversity statistic is then calculated for each plot, and then averaged by group. To optimally interpret patterns of diversity, plant life forms such as woody and herbaceous, trees and shrubs, should be considered separately in diversity studies (Huston 1994). While some actual or theoretical situations may cause commonly used diversity statistics to give contradictory results, for most sample data from natural communities the values for all diversity statistics are highly correlated (Huston 1994).

Following are some of the more common diversity statistic equations.

S = total number of species recorded
N = the total number of individuals summed for all S species (combined)

Margalef's diversity index (D_{Mg})

$$D_{Mg} = \frac{(S-1)}{\ln N}$$

Berger-Parker diversity index (d)

$$d = \frac{N_{\max}}{N}$$

where:
N_{max} = number of individuals for the most abundant species

To ensure the index increases with increasing diversity the reciprocal form of the measure is usually adopted (1/d).

Simpson's index (D)

$$D = \sum \frac{n_i(n_i - 1)}{N(N-1)}$$

where:
n_i = number of individuals in the i^{th} species

To ensure the index increases with increasing diversity the reciprocal form of the measure is usually adopted (1/D).

Shannon diversity index (H')

$$H' = \sum p_i (\ln p_i)$$

where:
p_i = proportional abundance of the i^{th} species (n_i / N)

Shannon evenness (E)

$$E = \frac{H'}{\ln S}$$

where:
H' = Shannon diversity index

The following general guidelines for diversity analyses are provided by Magurran (1988) and Southwood (1978):

(a) Ensure where possible that sample sizes are equal and large enough to be representative.

(b) Calculate the Margalef and Berger-Parker indices. These straightforward measures give a quick measure of the species abundance and dominance components of diversity. Their ease of calculation and interpretation is an important advantage.

(c) If one study is to be directly compared with another, the same diversity index should be used.

11.10.2 Similarity Coefficients

11.10.2.1 General Description

Similarity coefficients evaluate the relatedness of sites, communities, training areas, etc. Used in rangeland ecology to compare a single site to a *desired condition or status*, the analysis can be applied to any two sites, or groups of sites. There are a number of variations for the calculation of similarity coefficients. The USDA Forest Service (1996) recommends the Sorensen coefficient (Shimwell 1972):

$$\frac{2w}{a+b}$$

where a is the number of the constant (e.g., Cover-Frequency Index) of the first group, b is the number of the constant of the second group, and w is the number both have in common (i.e., the lowest of the two values for a specific condition). The point of separation between similarity and the lack of similarity at 65%; that is, there is similarity for values from 65-100% and a lack of similarity for values from 0-64%. However, 65% is an arbitrary value and professional judgement should be used to justify an increase or decrease of the cut-off value. If, for example, a comparison is made between a pristine site and a utilized site, based on the presence of the same dominant species, a cut-off of 60% may be more appropriate. Likewise, 70% may not be considered similar because of the species present and the species desired for the site. An understanding of composition and the ecology of a community type is necessary.

Another calculation for similarity is the Jaccard's Coefficient of Similarity (Shimwell 1972):

$$\frac{w}{a+b-w}\times 100$$

While similar to Sorensen's coefficient, Jaccard's calculation tends to be a lower value, and 50% is the general cut-off. Other indices of similarity are based on species presence, species dominance, and the combination of species present. The quality of one index describing similarity over another is hard to quantify.

11.10.2.2 Applicability

Similarity coefficients are used for comparing the degree of likeness. In general, cover and frequency data are used in combination as the constant for comparison; however, other descriptors can be used.

11.10.2.3 Advantages and Limitations

Similarity coefficients are easy to calculate; however, an understanding of the groups being compared is necessary to determine an applicable cut-off point. Also, there should be greater similarity within than between the groups being compared (i.e., greater similarity within a plant community type than between plant community types).

11.10.2.4 Example

The following example compares the community classification of five plots in a single training area to five plots in a "pristine" area within the Mojave desert. Both groups of plots are representative of the *Ambrosia dumosa/Larrea tridentata* (*AMDU2/LATR2*) vegetation type. The question is -- *How similar are plots in a disturbed area compared to an undisturbed, or control, area?*

1. Compile a data set to test species similarity between two locations with the same vegetation type. This can be two training areas with different uses. In the example, vegetation in a control site (treatment 1) is compared to that in a training area (treatment 2).

2. Calculate canopy cover (%) (Table 57). Display canopy cover by species, plot, and treatment (Table 58). Create a table displaying occurrence (presence or absence) of species by plot and treatment (Table 59). The value will be 1 or 0.

3. Calculate frequency (%) (Table 60). Frequency is the proportion or percent of plots in which a species occurs.

4. Calculate the average canopy cover (%) by species (Table 61).

5. Calculate Cover-Frequency Index (Table 62).

6. Determine similarity (Table 62).

7. Calculate Sorensen's and Jaccard's similarity indices (Table 62).

Canopy cover data are used in this example. Canopy cover consists of all plant life forms in a community and provides an indication of species dominance. Cover-Frequency Index values are typically the constant used in the description of similarity:

$$\text{Cover-Frequency Index} = \text{Average \% Canopy Cover} \times \text{\% Frequency}$$

Table 57. Canopy cover data from 5 plots in Training Area B.

Data are used to determine the similarity of 5 plots in Training Area B to 5 plots in a control area adjacent to the installation. All plots are representative of the *Ambrosia dumosa/Larrea tridentata* vegetation type. The number of canopy intercepts/ point/ species and the total number of canopy intercepts/line are given. The percent canopy cover for each species is shown as the number of intercepts for a species (*a*) divided by the total number of intercepts of all species (*b*) x 100.

PlotID	Locatio	VegID	Count (a)	Total Intercepts (b)	% Canopy Cover
4	Control	AMDU2	28	41	68.3
4	Control	ERBO	5	41	12.2
4	Control	LATR2	8	41	19.5
25	Control	AMDU2	8	13	61.5
25	Control	LATR2	5	13	38.5
27	Control	AMDU2	5	47	10.6
27	Control	BRTE	12	47	25.5
27	Control	GRSP	4	47	8.5
27	Control	LATR2	26	47	55.3
28	Control	AMDU2	9	17	52.9
28	Control	GRSP	1	17	5.9
28	Control	LATR2	6	17	35.3
28	Control	LYAN	1	17	5.9
54	Control	AMDU2	9	43	20.9
54	Control	CHPA12	7	43	16.3
54	Control	EPNE	1	43	2.3
54	Control	ERFAP	3	43	7.0
54	Control	LATR2	5	43	11.6
54	Control	SAME	14	43	32.6
54	Control	THMO	4	43	9.3
8	TrArea B	AMDU2	1	5	20.0
8	TrArea B	ERIN4	1	5	20.0
8	TrArea B	LATR2	3	5	60.0
18	TrArea B	AMDU2	2	15	13.3
18	TrArea B	EULA5	2	15	13.3
18	TrArea B	GRSP	3	15	20.0
18	TrArea B	LATR2	8	15	53.3
108	TrArea B	AMDU2	1	3	33.3
108	TrArea B	LATR2	2	3	66.7
114	TrArea B	STSP3	1	1	100.0
132	TrArea B	LATR2	2	3	66.7
132	TrArea B	LYAN	1	3	33.3

Table 58. Species canopy cover (%) by plot in *Ambrosia dumosa/Larrea tridentata* vegetation types in the control area and in Training Area B.

	Percent Canopy Cover										
	Control Area						Training Area B				
Species Code	plot 4	plot 25	plot 27	plot 28	plot 54		plot 8	plot 18	plot 108	plot 114	plot 132
AMDU2	68.3	61.5	10.6	52.9	20.9		20.0	13.3	33.3		
BRTE			25.5								
CHPA12					16.3						
EPNE					2.3						
ERBO	12.2										
ERFAP					7.0						
ERIN4							20.0				
EULA5								13.3			
GRSP			8.5	5.9				20.0			
LATR2	19.5	38.5	55.3	35.3	11.6		60.0	53.3	66.7		66.7
LYAN				5.9							33.3
SAME					32.6						
STSP3										100.0	
THMO					9.3						

Table 59. Presence of species on plots in the *Ambrosia dumosa/Larrea tridentata* vegetation types in a control area and in Training Area B.

	Occurrence										
	Control Plot #s						Training Area B Plot #s				
Species Code	4	25	27	28	54		8	18	108	114	132
AMDU2	1	1	1	1	1		1	1	1		
BRTE			1								
CHPA12					1						
EPNE					1						
ERBO	1										
ERFAP					1						
ERIN4							1				
EULA5								1			
GRSP			1	1				1			
LATR2	1	1	1	1	1		1	1	1		1
LYAN				1							1
SAME					1						
STSP3										1	
THMO					1						

Table 60. Species frequency (%) in *Ambrosia dumosa/Larrea tridentata* vegetation types in a control area and in Training Area B. Percent frequency is the number of plots where the species occurred divided by the number of plots surveyed X 100.

	Percent Frequency	
Species Code	**Control**	**Training Area**
AMDU2	100	60
BRTE	20	0
CHPA12	20	0
EPNE	20	0
ERBO	20	0
ERFAP	20	0
ERIN4	0	20
EULA5	0	20
GRSP	40	20
LATR2	100	80
LYAN	20	20
SAME	20	0
STSP3	0	20
THMO	20	0

Table 61. Average percent cover of species in *Ambrosia dumosa/Larrea tridentata* vegetation types in a control area and in Training Area B.

	Average Canopy Cover (%)	
Species Code	**Control**	**Training Area**
AMDU2	42.9	22.2
BRTE	25.5	0.0
CHPA12	16.3	0.0
EPNE	2.3	0.0
ERBO	12.2	0.0
ERFAP	7.0	0.0
ERIN4	0.0	20.0
EULA5	0.0	13.3
GRSP	7.2	20.0
LATR2	32.0	61.7
LYAN	5.9	33.3
SAME	32.6	0.0
STSP3	0.0	100.0
THMO	9.3	0.0

Table 62. Cover-Frequency Index (CFI) and similarity between the control area and Training Area B in *Ambrosia dumosa/Larrea tridentata* vegetation types.

Sorensen's and Jaccard's similarity indices are shown. Cover-frequency index values are canopy cover (Table x-2) X frequency (Table x-4). Similarity is the amount of commonness of the CFI values by species (the lowest of the two values).

	CFI		**Similarity**	
	Control	Training Area B		
Species Code	*a*	*b*	*w*	
AMDU2	4286.8	1333.3	1333.3	
BRTE	510.6	0.0	0.0	
CHPA12	325.6	0.0	0.0	
EPNE	46.5	0.0	0.0	
ERBO	243.9	0.0	0.0	
ERFAP	139.5	0.0	0.0	
ERIN4	0.0	400.0	0.0	
EULA5	0.0	266.7	0.0	
GRSP	287.9	400.0	0.0	
LATR2	3204.3	4933.3	0.0	
LYAN	117.6	666.7	0.0	
SAME	651.2	0.0	0.0	
STSP3	0.0	2000.0	0.0	
THMO	186.0	0.0	0.0	
Sum	10000.0	10000.0	1333.3	
	Sorensen	$(2w/a+b)*100$		13.3
	Jaccard	$(w/a+b-w)*100$		7.1

Results. Each equation gives a different value. Whether there is dissimilarity or similarity depends on the cut-off level. Sorensen uses 65% and Jaccard uses 50%. Both tests indicate dissimilarity between the two vegetation types. That is, given the control area and Training Area B were similar prior to military and other possible uses, they have changed with use.

11.10.3 Importance Values

11.10.3.1 General Description

Importance values are the summation of a number of measures describing characteristics of a species on a plot, in a training area, in a community, or on an installation. A single measure (e.g., cover, frequency, or density) may inadequately describe the role of a species. An importance value is a comprehensive index, generally consisting of 1) relative frequency (the frequency of a species as a percent of the total frequency value of all species within the sampling unit), plus 2) relative density (the density of a species as a percent of the total density of all species), plus 3) relative dominance, or cover, of a species (the cover of a species as a percent of the total area measured). Other measures can be included in determining a importance values, such as production or volume.

11.10.3.2 Applicability

Importance values can be used as the sum or as the average of two or more descriptive characteristics of species to describe the significance of a species to other species present.

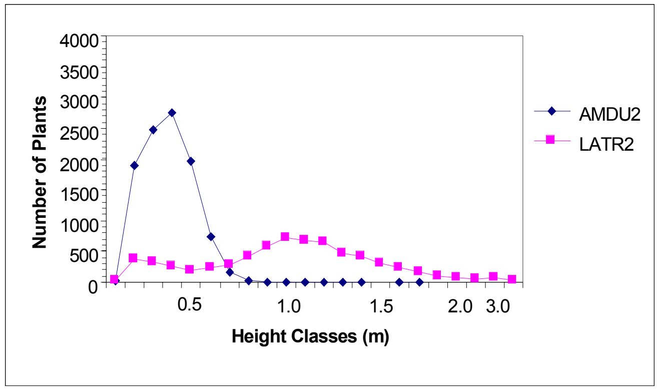
11.10.3.3 Advantages and limitations

Care must be exercised when choosing the attributes used to calculate importance values. Importance values can end-up being arbitrary and not truly descriptive of a species role. Combined measures should be used critically (Greig-Smith 1983).

11.10.3.4 Example

The following example compares woody plant data collected on 210 transects. Data for the two dominant species, *Ambrosia dumosa* and *Larrea tridentata* are shown and compared. Both species are components of community types in the Sonoran desert. *Ambrosia* is noted for its density (Figure 145A) and *Larrea* for its visual dominance (Figure 145B).

A.



B.

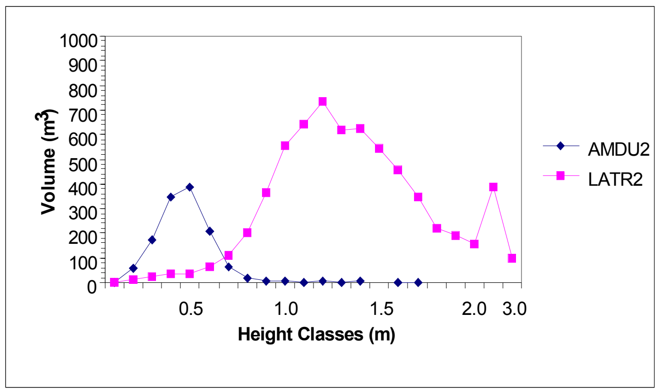


Figure 145. A. The distribution of *Ambrosia dumosa* and *Larrea tridentata* in the Sonoran desert. B. The distribution of *Ambrosia dumosa* and *Larrea tridentata* volume.

To calculate the importance values for these two species:

1) Calculate species density: Density = number of individuals/sample area

2) Calculate relative density

Relative Density = (the density for a species / total density of all species) X 100

3) Calculate species frequency

Frequency = number of plots where a species occurs / number of plots sampled

4) Calculate the relative frequency

Relative Frequency = frequency of a species /total frequency of all species X 100

5) Calculate species dominance, or volume[5]

Dominance = volume of a species / area sampled

6) Calculate the relative dominance

Relative Dominance = (dominance of a species / total dominance of all species) x 100

7) Calculate the importance value (IV)

Relative Density + Relative Frequency + Relative Dominance / number of components

In the example shown below, the number of components is three.

	Relative Density	Relative Frequency	Relative Dominance	Importance Value (IV)
AMDU	49.1	15.6	5.0	23.2
LATR2	33.1	11.2	43.2	29.2

Results -- *Ambrosia* is more abundant (Relative Density), occurs on more plots (Relative Frequency), but is much smaller (Relative Dominance) than *Larrea*. Because of number and the greater occurrence of *Ambrosia*, even with its smaller size, *Ambrosia* is only slightly less important than *Larrea.*

11.11 Software for Statistical Analysis

There are a number of software packages available for statistical analysis on personal computers (PCs). They are typically divided into three basic categories: a) spreadsheets and add-ins for commercial spreadsheets; pseudo-spreadsheet and menu-driven packages; and c) command line, programmable packages. This section provides a summary of the packages that are currently available. Versions, features, and prices change rapidly; this discussion does not represent an endorsement of any particular product.

[5] In this example, plants are considered to be spheres. Therefore, volume was calculated as height X Πr^2; where r = 0.5 x height. (See Bonham 1989 for a detailed discussion on plant shapes and volumes).

The relative advantages and disadvantages of these three approaches are listed in Table 63.

Table 63. Relative advantages and disadvantages of statistical software types.

Type of package	Advantages	Disadvantages
Spreadsheet	1. Easy to use. 2. Short learning curve for implementing simple functions. 3. Programming capabilities.	1. Limited Capabilities 2. Difficult and tedious to implement for complex data models. 3. May be tedious to repeat complex analysis on several datasets. 4. Will not do most types of multivariate analysis.
Spreadsheet Add-in	1. Fairly easy to use. 2. Short learning curve for implementing simple functions. 3. Programming capabilities. 4. Fairly easy to repeat complex analysis on several datasets.	1. Somewhat limited capabilities. 2. Additional expense on top of spreadsheets. 3. Will not do most types of multivariate analysis.
Pseudo-spreadsheets	1. Fairly easy to use. 2. Some programming capabilities 3. Fairly easy to repeat complex analysis on several datasets. 4. Will perform many types of multivariate analysis.	1. Moderate learning curve. 2. Requires a more thorough understanding of statistical techniques and theory.
Command line	1. Very Powerful. 2. Good documentation of statistical techniques. 3. Will perform virtually all types of multivariate analysis. 4. Programmable with a flexible, very powerful programming language.	1. Substantial learning curve involved 2. Requires a more thorough understanding of statistical techniques and theory. 3. Can be expensive, but it depends on the package you choose.

11.11.1 Spreadsheets and Add-ins

Commercial spreadsheets like Excel, Quatro Pro, and Lotus 1-2-3 have a number of statistical capabilities built into them. Refer to Table 64 and Table 65 for a summary of built-in capabilities.

Table 64. Statistical tests/functions for spreadsheet add-ins and spreadsheet software packages.

	Spreadsheet add-ins			Spreadsheets		
statistical tests/functions	WinStat	Analyse-It	XLStat	Excel	Quattro Pro	Lotus 1-2-3
Descriptive statistics	x	x	x	x	x	x
t-test	x	x	x	x	x	x
Correlations	x	x	x	x	x	x
Regressions	x	x	x	x	x	x
Analysis of variance	x	x	x	x	x	x
Bootstrapping						
Canonical corellations						
Cluster analysis	x		x			
Correspondence analysis			x			
Discriminant analysis	x		x			
Factor analysis	x		x			
Multiple comparisons	x		x			
Nonparametric tests		x	x			
Principal component analysis			x			
Programmable*	3	3	3	3	3	3
Current version	due Spring, 1999	not listed	3.5	97	8.0	9.0

* The numbers 1-3 in the *programmable* row of Table 64 indicate three levels of programmability. A "1" indicates that the package uses its own command line-type program language and that highly complex and interactive programs can be written to run the package. Learning and understanding the programming language is usually necessary in order to use the package effectively. A "2" means that the package allows one to set up "scenarios" that can then be applied to other datasets of similar or identical structure. This is particularly useful if one wants to perform the same tests on a series of different datasets. A "3" indicates that the package also has its own program language available, however the programming environment is quite different from that defined by the number 1. Rather than being command line driven, code is associated with cells within the spreadsheet or is tied to buttons or forms that one inserts onto the spreadsheet. An example is *Visual Basic for Applications*, which is used with Excel 97.

Table 65. Statistical tests/functions for command line and pseudo-spreadsheet statistical software packages.

	Command line packages				Pseudo-spreadsheets			
statistical tests/functions	SPSS	BMDP	SAS	S-Plus	Systat	SigmaStat	Statview	Minitab
Descriptive statistics	x	x	x	x	x	x	x	x
t-test	x	x	x	x	x	x	x	x
Correlations	x	x	x	x	x	x	x	x
Regressions	x	x	x	x	x	x	x	x
Analysis of variance	x	x	x	x	x	x	x	x
Bootstrapping	x	x	x	x	x			
Canonical correlations	x	x	x	x				
Cluster analysis	x	x	x	x	x			x
Correspondence analysis	x	x	x	x	x			x
Discriminant analysis	x	x	x	x	x			x
Factor analysis	x	x	x	x	x			x
Multiple comparisons	x	x	x	x	x	x		
Nonparametric tests	x	x	x	x	x	x		x
Principal component analysis	x	x	x	x	x			x
Programmable	1	1	1	1	2	2	2	2
Current version	8.0	7.0	6.12	4.5	8.0	2.0	5	12.21

Add-in packages are tool sets that are added to spreadsheets to expand their capability. For example, Excel 97 has an "add-in manager " that allows a user to change from one add-in tool set to another. In the case of these add-ins, new features and functions are added to the functions already within the package. The add-ins are available only after the spreadsheet is opened. Running the statistics does not require you to open a separate piece of software. However, several steps must be performed within the spreadsheet in order to load the new functions.

11.11.2 Command-Line and Pseudo-Spreadsheets

The term "command line" refers more to the origin of the programs than to how they are currently executed. All four of these packages began as software programs installed on mainframe computers running UNIX or some other operating system. They have evolved to their present state and still can be run in a "command line" environment. This means that a user can execute commands from a command prompt, one line at a time. However, most of these packages also have various levels of interactivity built into them. For example, the SAS language allows one to insert commands and functions directly from a series of help tools. BMDP now comes with a highly integrated graphical user interface that marks it as more of a hybrid statistics tool, integrating the command line environment with a graphical user interface.

The term “pseudo-spreadsheets” refers to how the user organizes and views data; it does not refer to how data are entered or edited. These packages allow a user to input or import data in rows and columns and view data in a manner very similar to a spreadsheet. However, the similarity stops here. Most do not allow the user to manipulate the data with the same ease as spreadsheets. The data are not technically stored in “cells” as they are in spreadsheets, so one cannot generally reference data in a specific cell.

11.11.3 Graphics Capabilities

All of the aforementioned packages provide the ability to prepare graphs of your data and results. Some are highly interactive (e.g. Excel, Quattro, Lotus) whereas others are extremely powerful but not very user-friendly (e.g. SAS). Those in the middle can prepare graphs to meet most needs. SigmaStat appears to produce very high-quality graphics. It is an interactive tool that integrates well with Excel spreadsheet data. It requires that SigmaPlot (SPSS) software, a scientific graphics tool, be running concurrently.

11.11.4 Selecting a Package

Trying to choose a database package can be challenging. Just like in buying a car or anything else for that matter, it all depends on what you want to do with it. Most (all?) of the companies offer free trial versions of the software so you can “try before you buy”. It would be an excellent idea to do this if you have the time. Cost for these packages varies depending on the buying programs that are in place at your place of work. Check with your purchasing group first to see if they have pre-negotiated discounts for any of the packages.

Users interested in programming and complex statistics should consider any of the four “command line” systems. Users are most likely to achieve success with complex software packages if they have access to good customer support or other experienced users where they work. A local user-group may be helpful for support. In the absence of any local users, you may want to base your choice on the quality of technical support and documentation provided by the company.

For less-advanced users, any of the “pseudo spreadsheet” packages should prove adequate. When a number of packages have similar features, the preferred software is often that which the user is familiar with. If principal needs consist of descriptive statistics, t tests, Analysis of Variance, or similar functions, any popular spreadsheet or basic statistical package should suffice.

11.11.5 Sample Size and Power Analysis Software

Sample size adequacy and power analysis are important when planning or evaluating a study. Sample sizes, statistical power, and minimum detectable change sizes can be calculated using tables, charts, calculators, and spreadsheets (see Chapter 3 for equations). However, computer software can in some cases improve accuracy and ease of calculation. Sample size calculators and power analysis has been incorporated into several statistical software packages, but is generally treated as a separate module for an additional cost.

Thomas and Krebs (1997) provide a critical review of statistical power analysis software. All software reviewed is constantly in development; features, cost, support, and ease of use therefore are also constantly changing. For beginner to intermediate level use, they recommend one of the commercial general purpose power packages: NQUERY ADVISOR (mailto:info@statsolUSA.com), PASS, or STAT POWER (mailto:QEISys@aol.com). Additional commercial packages with potential include POWER AND PRECISION (http://www.PowerAndPrecision.com) and EX-SAMPLE (http://www.ideaworks.com). A number of freeware and shareware programs were also reviewed. Among these programs, those that had the highest ratings include GPOWER (http://www.psychologie.uni-trier.de:8000/ projects/gpower.html), POWER PLANT (mailto:biometrics@ccmar.csiro.au), STPLAN (ftp://odin.mdacc.tmc.edu/pub/msdos/stplan41.exe - survival analysis and medical statistics), MONITOR (ftp://ftp.im.nbs.gov/pub/software/monitor - population trend analysis), and TRENDS (ftp://ftp.im.nbs.gov/pub/software/CSE/wsb21515/trends.zip - population trend analysis). The authors concluded that most general purpose statistical programs reviewed were inadequate in one or more respects. Elzinga et al. (1998) reviewed a number software programs following the review by Thomas and Krebs. They recommend the programs STPLAN (freeware) and PC SIZE: CONSULTANT (ftp://ftp.simtel.net/pub/simtelnet/msdos/statstcs/size102.zip - shareware). They do not recommend GPOWER for vegetation monitoring applications due to limited software documentation and a high level of assumed knowledge.

The review by Thomas and Krebs (1997) is available at http://sustain.forestry.ubc.ca/cacb/power/review/review.html. The USGS maintains a World Wide Web page with power analysis information and links to software and on-line calculators at: http://www.mp1-pwrc.usgs.gov/powcase/powlinks.html. A comprehensive list of microcomputer software for calculating power analysis is maintained by L. Thomas at: http://sustain.forestry.ubc.ca/cacb/power/.

11.12 Spreadsheet Tools and Functions in Microsoft Excel

The following section provides some basic instruction on programming equations and functions in Excel. Examples of elementary statistical analyses are contained in a spreadsheet file named "Statistical Analysis and Data Manipulation Examples.xls", which is available on the Center for Ecological Management of Military Lands (CEMML) web site (www.cemml.colostate.edu/trm/index.htm).

11.12.1 Using Functions in Excel

There are a wide number of functions available in Excel for performing data analysis. This section provides a short tutorial on how use functions and write equations in Excel worksheets. Much of the following information is taken from the Microsoft Office 97 Professional Excel *Help* function, which can be accessed by clicking on the <Help> menu and then the ***<Contents and Index>*** option on the Excel97 menu. Under the ***<Index>*** tab, try typing in the keyword ***<functions>***, and browse some of the sections that come into view.

Statistical worksheet functions perform statistical analysis on sets of data. For example, a function can provide statistical information about a straight line plotted through a group of values, such as the slope of the line and the y-intercept, or about the actual points that make up the straight line. Table 66 summarizes some of the basic statistical functions available.

The following section provides some basic instruction on programming equations and functions in Excel. Examples of elementary statistical analyses arecontained in a spreadsheet file named "Statistical Analysis and Data Manipulation Examples.xls", which is available on the CEMML web site (www.cemml.colostate.edu/trm/index.htm).

Table 66. Some of the statistical functions available in Excel.

Sum	The sum of the values. This is the default function for numeric source data.
Count	The number of items. The Count summary function works the same as the COUNTA worksheet function. Count is the default function for source data other than numbers.
Average	The average of the values.
Max	The largest value.
Min	The smallest value.
Product	The product of the values.
Count Nums	The number of rows that contain numeric data. The Count Nums summary function works the same as the COUNT worksheet function.
StdDev	An estimate of the standard deviation of a population, where the sample is all of the data to be summarized.
StdDevp	The standard deviation of a population, where the population is all of the data to be summarized.
Var	An estimate of the variance of a population, where the sample is all of the data to be summarized.
Varp	The variance of a population, where the population is all of the data to be summarized.

11.12.1.1 Using Functions to Calculate Values

Functions are predefined formulas that perform calculations by using specific values, called arguments, in a particular order, called the syntax. For example, the SUM function adds values or ranges of cells, and the PMT function calculates the loan payments based on an interest rate, the length of the loan, and the principal amount of the loan. Arguments can be numbers, text, logical values such as TRUE or FALSE, arrays, error values such as #N/A, or cell references. The argument you designate must produce a valid value for that argument. Arguments can also be constants, formulas, or other functions. The syntax of a function (Figure 146) begins with the function name, followed by an opening parenthesis, the arguments for the function separated by commas, and a closing parenthesis. If the function starts a formula, type an equal sign (=) before the function name. As you create a formula that contains a function, the Formula Palette will assist you.

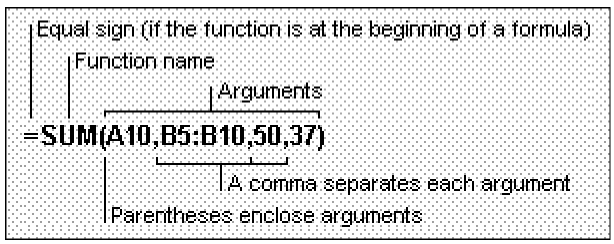


Figure 146. Syntax of a typical Excel function.

11.12.1.2 How Formulae Calculate Values

A formula is an equation that analyzes data on a worksheet. Formulas perform operations such as addition, multiplication, and comparison on worksheet values; they can also combine values. Formulas can refer to other cells on the same worksheet, cells on other sheets in the same workbook, or cells on sheets in other workbooks. Figure 147 shows a formula which adds the value of cell B4 and "25" and then divides the result by the sum of cells D5, E5, and F5.

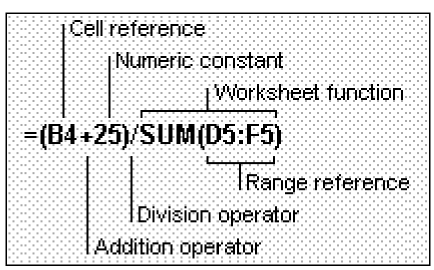


Figure 147. Sample formula used in Excel.

Formulas calculate values in a specific order that is known as the syntax. The syntax of the formula describes the process of the calculation. A formula in Microsoft Excel begins with an equal sign (=), followed by what the formula calculates. For example, the following formula subtracts 1 from 5. The result of the formula is then displayed in the cell:

$$= (5-1)$$

11.12.1.3 Examples of Functions

To demonstrate their most useful features, we are using an example from a military base in the Southeastern U.S. The data file contains precipitation data from a local meteorological station. Table 67 shows a subset of the data to give the reader an example of what the data look like.

In the first example we will convert the precipitation level from inches to millimeters. There are 25.4 millimeters per inch. The first cell containing precipitation data is **C2**, and the total precipitation in millimeters needs to be written to cell **D2**. In cell **D2**, the following equation should be written:

=(C2)*25.4

Table 67 . Subset of precipitation data used in example.

YEAR	WEEK	PRECIP (in.)
65	1	0.20
65	2	0.40
65	3	1.10
65	4	0.45
65	5	1.49
…	…	…

The equation from cell **D2** can be copied and pasted to all of the other cells for which the conversion should be made. The copy operation will automatically update the cell address for each cell, so that for cell **D3**, the equation is changed to

=(**C3**)*25.4

and so on for the 1655 lines of data in the worksheet (Table 68).

Table 68. Resulting spreadsheet showing the conversion from inches to millimeters.

YEAR	WEEK	PRECIP (in.)	PRECIP (mm)
65	1	0.20	5.08
65	2	0.40	10.16
65	3	1.10	27.94
65	4	0.45	11.43
…	…	…	…

The next example uses the SUM function to add up all of the data for a single year using the sum function. We are interested in seeing the total precipitation over a two-year period- the 1982 El-Nino year and the following year. The sum function calculates the totals for a range of cells specified in the function. In this case, the cell range to be totaled for 1982 runs from **D890** to **D941**. The equation looks like this:

=sum(**D890**:**D941**)

The keyboard can be used to build cell ranges. The following keystrokes are used:

1. In the target cell for the equation (**E941**), type in the following characters: =sum(The left parenthesis is the code that Excel interprets as the beginning of the function's arguments.

2. Press the left arrow key once, moving the cursor to cell **D941**. You will notice that the cell is now surrounded by an animated, rotating dotted line.

3. Press and hold the shift key, and using the up arrow key, move the cursor to the top of the range of cells that you wish to add. The animated, dotted line will move to outline the entire range. You can also do this by putting the mouse cursor on the beginning of the cell range, pressing the left mouse button, and dragging the cursor to the other end of the range, letting up on the left mouse button when you reach the end of the range.

4. Press the right parenthesis key to close the function, and press the enter key. The function has now been programmed.

Repeating these steps for the 1983 data, we find that the year following the El Nino summer brought 1398.78 mm of precipitation, compared with 827.02 mm for the El Nino year. As a shortcut, you may simply copy the contents of cell **E941** to cell **E993**, and Excel will automatically update the cell addresses to reflect the change in cell location.

11.12.2 Pivot Tables

Pivot tables, sometimes called *cross-tabulation tables/queries*, are very useful for manipulating tabular data within spreadsheets. They are particularly good at summarizing large volumes of data into easily interpretable data matrices.

This example uses the precipitation data from the previous section on functions and formulas. Let's propose that you would like to know what periods of year are most likely to be dry, so that tracked-vehicle maneuvers can be concentrated in those time periods in order to reduce potential erosion.

Two possible ways to answer this question are to calculate the average precipitation for each week of the year, or to calculate the probability that significant amounts of rain will fall for each week of the year.

11.12.2.1 Example: Summarizing Long-term Climatic Data

The raw data provided by the National Weather Service are shown in Table 69.

Table 69. Tabular precipitation data for the pivot table example. The data were provided for the periods 1965 to 1997.

YEAR	WEEK	PRECIP (in.)	PRECIP (mm)
65	1	0.20	5.08
65	2	0.40	10.16
65	3	1.10	27.94
65	4	0.45	11.43
65	5	1.49	37.85
65	6	0.96	24.38
65	7	3.09	78.49
65	8	0.35	8.89
65	9	1.19	30.23
65	10	2.13	54.10
65	13	0.12	3.05
…	…	…	…

The challenge immediately presented is: how to sum the data by week over the 32 year period? One approach is to go through and copy the data year-by-year into a large matrix, with the rows defined by the year and the columns defined by the weeks, and then program a cell to compute the average precipitation for each week. This is straightforward but takes a lot of time and is prone to manual errors. The more direct and efficient way to do it is through a pivot table.

Excel offers a wizard that automatically builds a pivot table based on input criteria. Following are some examples how to build a pivot table from the precipitation data.

Step 1. Open the workbook which contains the raw data. Click on the cell in the spreadsheet where you wish to place the pivot table. On the Data menu, click PivotTable Report. The dialog box in Figure 148 will appear. Select the Microsoft Excel list or database as your data source. Click on the **Next** button.

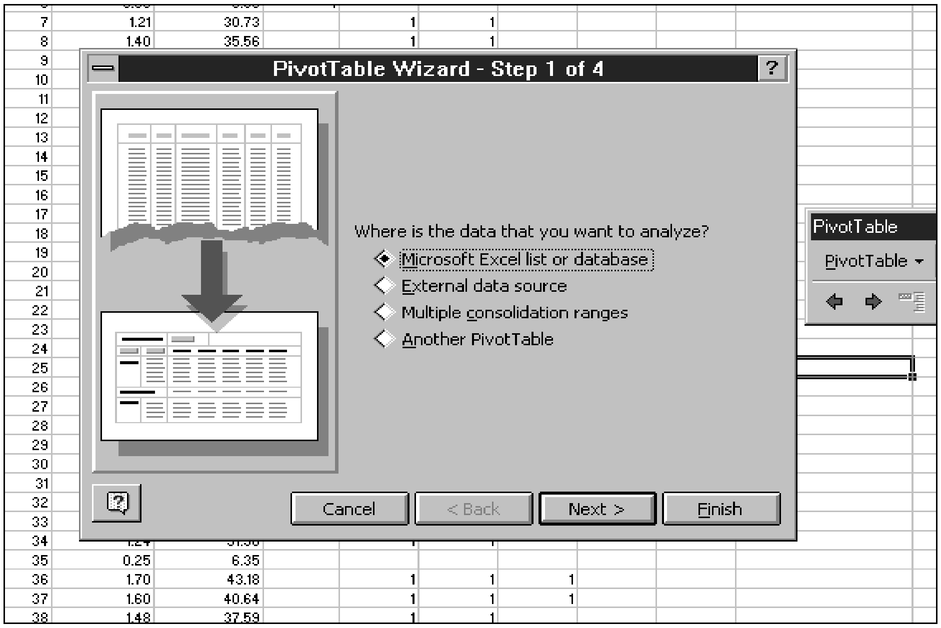


Figure 148. The first dialog box that appears when preparing a pivot table using the pivot table wizard.

Step 2. Using the mouse, click on the upper left corner of the range of cells you wish to use as the input source. Then, while holding down the left button on the mouse, drag the mouse cursor to the bottom right corner of the cell range you wish to use. In this case the cells are A3 through D1647. If you have column titles (as in this example) then you will want to make sure the column titles are in the very first row of raw data that you define for the pivot table. The dialog box will then look as in Figure 149. The input range is surrounded by a dashed-line box. Click on the **Next** button.

Step 3. Define the columns, rows, and cell contents for the pivot table. In this case we are trying to create a table with the columns defined as the weeks of the year and the precipitation data being the actual contents of the cell. You do this by dragging the **week** button into the section of the wizard labeled **COLUMN**, and by dragging the **Precip(mm)** button onto the section labeled **DATA**. Note that the dialog box in the **DATA** section will end up reading **sum of Precip(mm)**. To change this to calculate the mean, double-click on the **DATA** section and change the **Summarize By**… section to read **average** rather than **sum** (Figure 150).

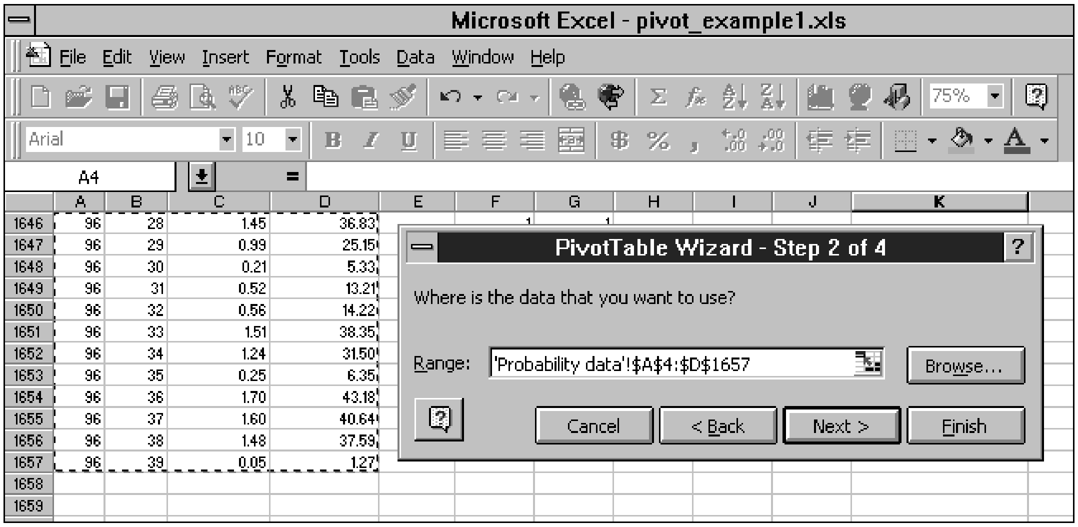


Figure 149. Step 2 in the pivot table wizard.

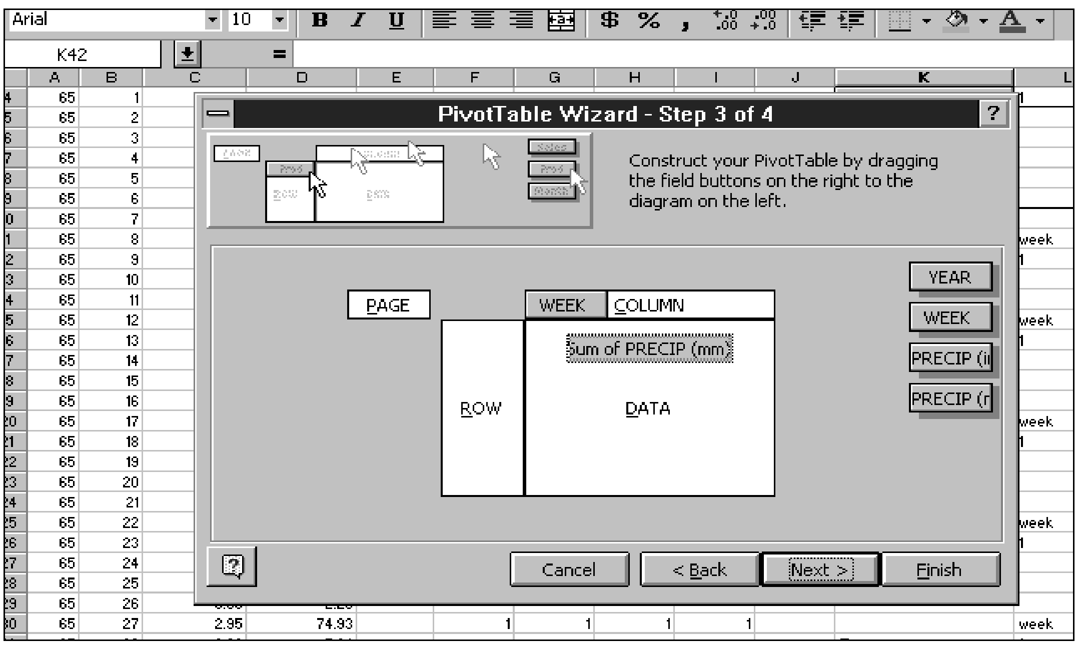


Figure 150. Step 3 in the pivot table wizard.

Step 4. At this point you will see the dialog box shown in Figure 151. Click on the cell in the spreadsheet where you wish the pivot table to be created, and then click on the **Finish** button. Excel will then paste the pivot table in place and calculate the averages for you.

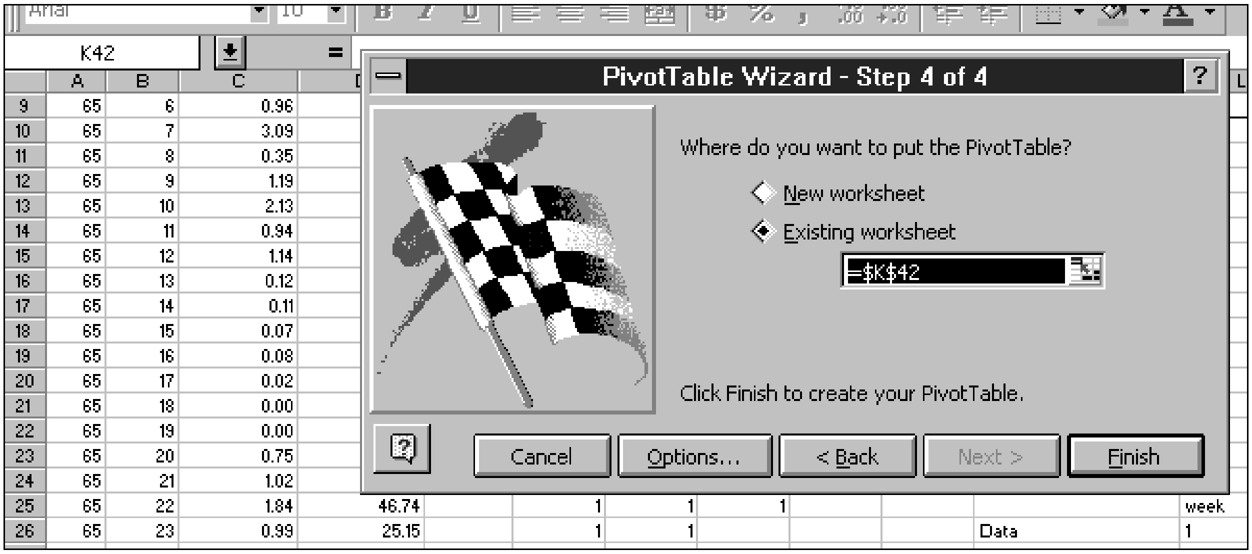


Figure 151. Final step in producing a pivot table from the pivot table wizard.

The results of the analysis (precipitation in mm for each week of the year) are shown in Figure 152. One can see that a week-by-week compilation of the data, with all of the associated cutting, pasting, and copying, would be a pretty large undertaking. Pivot tables can cut the time required by an order of magnitude or more, and have numerous applications beyond the example provided.

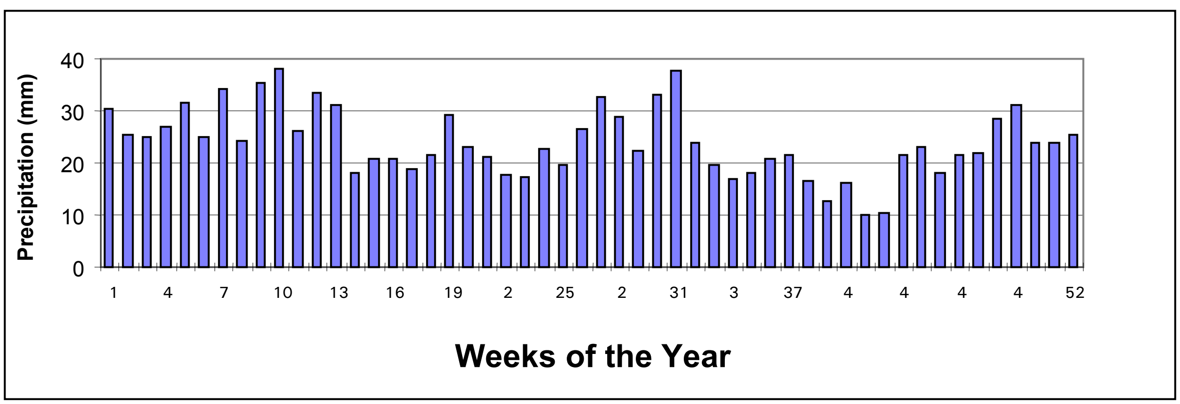


Figure 152. Results of the pivot table analysis, shown as mean weekly precipitation in mm for each week of the year.

11.12.3 Importing and Exporting Dbase and ASCII Text Files

When working with large volumes of data, one frequently is required to import information from other users or agencies, or export data for another party in your office to use in a different application, examples being ARC/INFO or Microsoft Access. The two most common denominators for exports and imports are dbase (.dbf) and ASCII (.txt) files. Most software used for data management and analysis (including Quest, SQLBase, Access, Paradox, SAS, SYSTAT, Statview, and others) will import and export data in these two formats. Many software applications will also import data from Excel files, but will not support files from the most recent versions of Excel. This section will provide a brief explanation on the steps required to export in dbase and ASCII formats.

11.12.3.1 Exporting and Importing Dbase Files

Dbase files have a number of limitations that should be taken into account during import and export operations. Field (column) names must be limited to 10 characters. Any portion of the column name after character 10 will be truncated. In Addition to this, portions of cells beyond the right margin of the cell will be automatically truncated by Excel during the export process. For example, a six character vegetation code like "PSMEME" within a column only four characters wide will be exported as PSME. For this reason we strongly recommend that all columns be expanded to their maximum width prior to exporting to dbase format.

There are other issues related to importing dbase files. Excel limits the maximum cell size of imported files to 255 characters, whereas dbase memo columns can contain over 65,000 characters. Excel will truncate all information after 255 characters. It is also important to note that dbase memo field information is stored separately in an associated ".dbt" file with the same name prefix as the ".dbf" file.

To import an Excel worksheet in dbase format, follow these steps:

1. Select the <File> menu and then the ***<open>*** function. On the ***<Open>*** dialog box that appears (Figure 153), specify ***<dbase Files (*.dbf)>*** under ***<Files of Type>*** in the lower left corner of the box, and then specify the name of the file you wish to import. Click on the ***<open>*** button, and the file will appear.

2. Make whatever changes or manipulations you need to the worksheet. When you are finished and are ready to save your work, click on the ***<File>*** menu and select the ***<Save as>*** function. The ***<Save as>*** dialog box then appears on the screen. You must specify in the ***<Save as type>*** field of the ***<Save As>*** dialog box that you wish

to save your work as a spreadsheet, rather than as a .dbf file (Figure 154). Then click on the ***<Save>*** button to save the file.

To Export an Excel worksheet in dbase format, one follows the steps similar to #2 above. One may save the entire contents of a worksheet or just a specific portion of the worksheet. To save the entire contents of the worksheet as a dbase file, make sure that one of the cells with actual data in it are selected by the cursor. If the cursor is on a cell is outside the range of cells that actually contain data, then Excel will register an error and not be able to export the actual data. To export just a portion of the worksheet, highlight the cells that you wish to export and then to through the steps that follow.

Specify ***<dbase IV>*** in the ***<Save as type>*** field of the ***<Save As>*** dialog box. Specify the name of the file that you wish to export (e.g. PLOTMAST.DBF), and then click on the ***<Save>*** button to export the file. The dialog box in Figure 155 will then appear. This simply indicates that the program will only export the data from the single worksheet on the screen. Data from other worksheets in the same Excel file will not be exported in this operation. Remember to make sure that all of your column widths are set to be at least as wide as the widest record in that column.

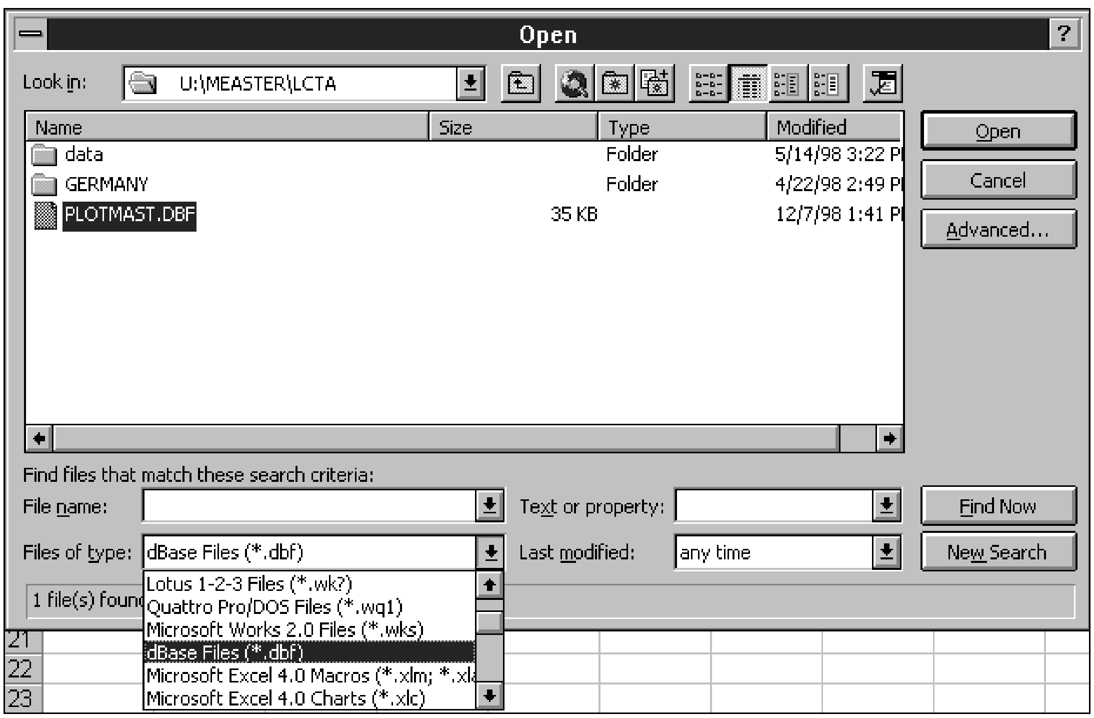


Figure 153. Dialog box used to import (<Open>) dbase file types into an Excel Worksheet.

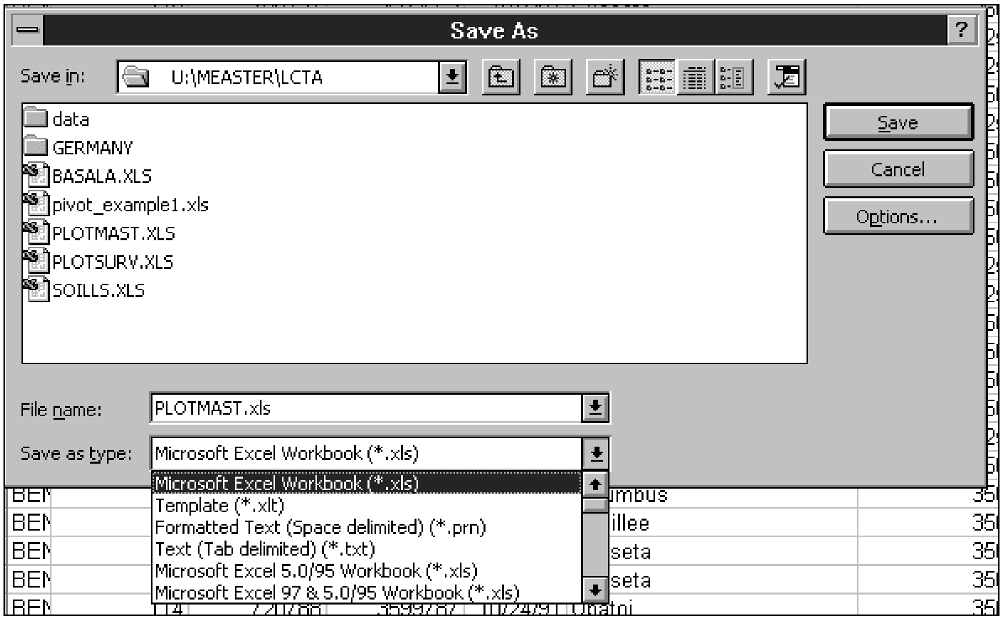


Figure 154. Dialog box used to export (<Save as>) imported dbase data into an Excel worksheet file.

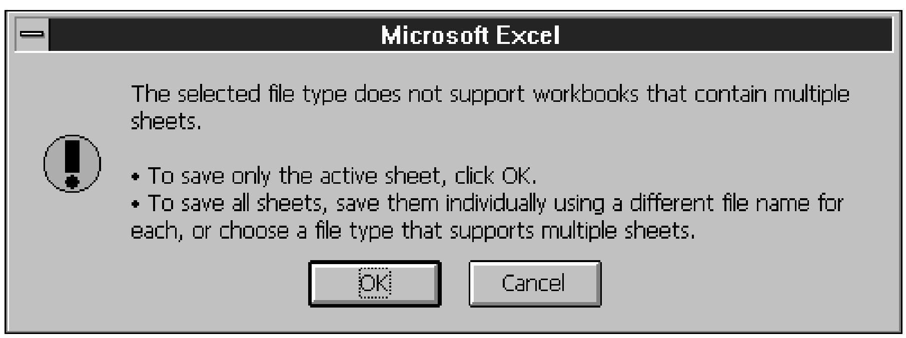


Figure 155. Dialog box that appears when saving in dbase and ASCII text file formats.

11.12.3.2 Exporting and Importing ASCII (text) Files

Sharing ASCII (text) files is another method to share information across different software programs. Text files are typically delimited by commas or tabs, and text data are differentiated from numerical data by surrounding text fields with double quotation marks. Whereas differentiating between data types using quotation marks is not necessary when importing into an Excel worksheet, it can be useful in some types of analysis and is generally recommended.

The steps for importing and exporting ASCII text files are nearly identical to those for dbase files. The only differences are:

- Specify the ***<Text>*** file type in the ***<Files of type>*** field in the ***<Open>*** dialog box when importing.

- Specify the ***<Text>*** file type in the ***<Save as type>*** field in the ***<Save as>*** dialog box when exporting.

11.12.4 Basic Statistical Tools in Excel

Excel has a large number of statistical functions available to it for various statistical analysis. This section reviews a number of the techniques available and provides examples.

It is very important that users understand the statistical tests that they are implementing within Excel. The creators of Excel have provided a number of powerful, easy-to-use statistical functions within the application. Unfortunately, it is easy to unintentionally misuse the tools, leading to inappropriate interpretations of the data analysis and incorrect management decisions based on those interpretations. We encourage the reader to refer to sections 3.1 and the remainder of section 11 for more information on statistical comparisons, and to consult with a professional statistician and/or a statistics textbook for more details on techniques if you are not familiar with them.

11.12.4.1 Descriptive Statistics

It is often desirable to describe a dataset in terms of means, standard deviations, and other statistical measures. One can request a set of statistics from Excel that describe the dataset in terms of means, variance, median, standard deviation, etc. To do so, select the <Tools> menu and then the ***<Data Analysis>*** option. Select ***<Descriptive Statistics>*** from the dialog box that appears and select ***<OK>***, and the dialog box in Figure 156 will appear.

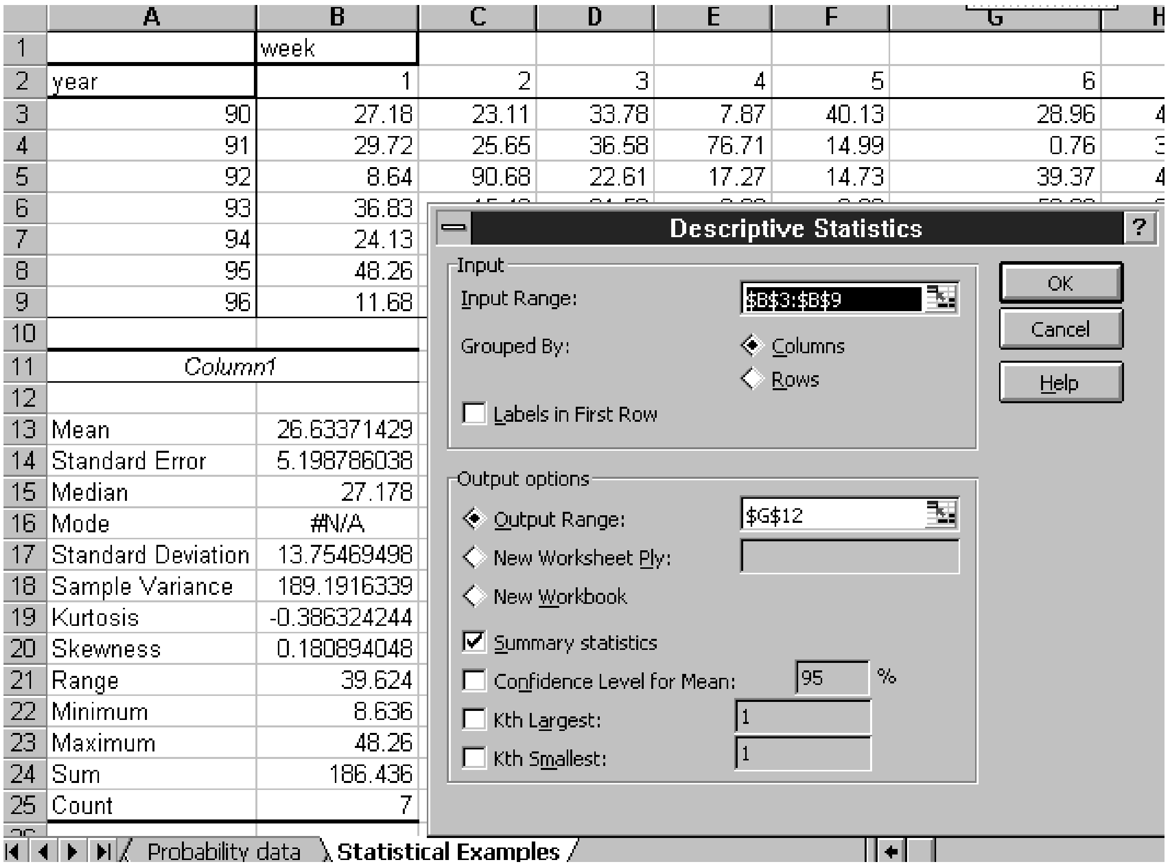


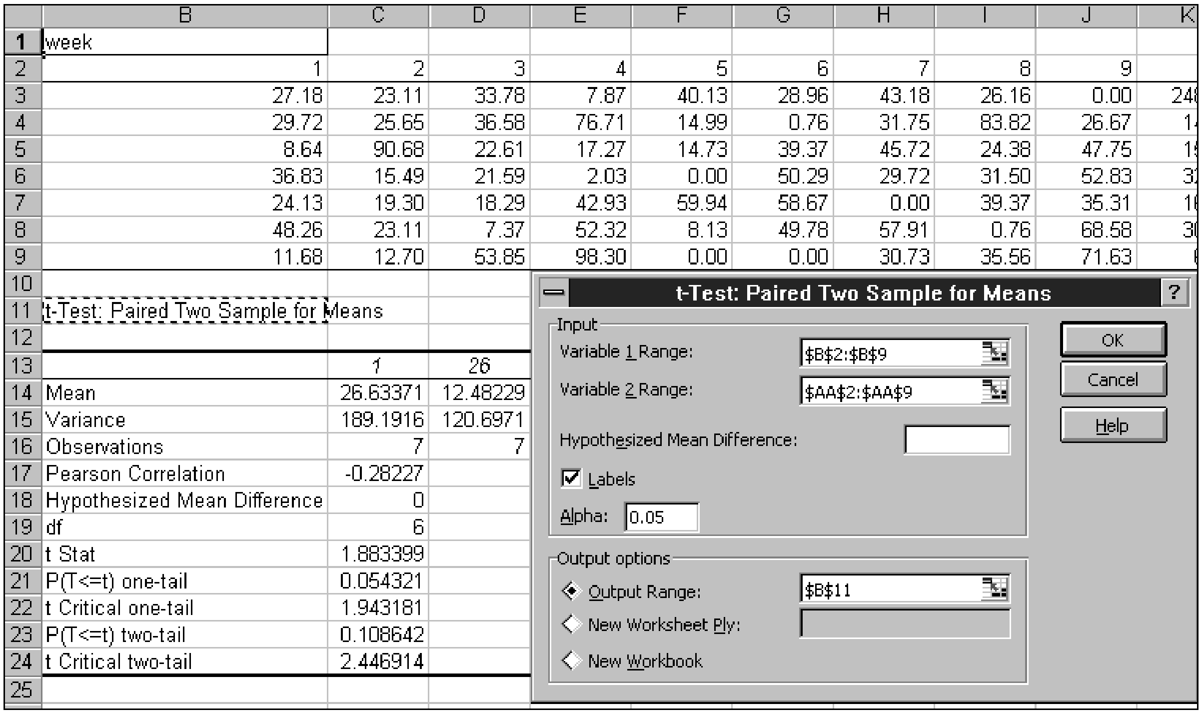
Figure 156. Dialog box for descriptive statistics in Excel.

In this case we specified the data from week 1 (cells B3-B9) for the analysis, and asked Excel to write the output to cell G12 under the output options. We also asked for summary statistics, in the bottom left corner of the dialog box. After clicking on the ***<OK>*** button on the dialog box, the output labeled ***<Column1>*** appeared.

11.12.4.2 T-Test

This is perhaps one of the most simple and basic statistical tests for making comparisons. As an example, let us use a portion of the dataset from the pivot table example. We will compare the average winter precipitation from the first week of the year with the average precipitation from week 26 in mid summer, from the years 1990-1996.

Just as in defining the descriptive statistics, select ***<Data Analysis>*** from the <Tools> menu, and then select ***<t-test: Paired Two Sample for Means>*** from the dialog box. The dialog box shown in Figure 157will appear. In this case we defined the two datasets being compared as that for weeks 1 and 26. We specified the data range of B2-B9, which includes the column labels, and checked the "labels" box in the center left portion of the dialog box to indicate that the first column in the data contains the column header/label. Next we specified an alpha level of .05, which is standard for most cases of physical and biological data comparisons. Finally, we specified the output range would be cell A11 in the bottom left corner of the dialog box, and then clicked on the “OK” button. The results of the analysis show that for a single-tailed comparison (appropriate in this case), the probability that the two are different is .054, or just over the .05 alpha level specified. Hence, the two samples are not statistically different in this comparison.



	B	C	D	E	F	G	H	I	J	K
1	week									
2	1	2	3	4	5	6	7	8	9	
3	27.18	23.11	33.78	7.87	40.13	28.96	43.18	26.16	0.00	24
4	29.72	25.65	36.58	76.71	14.99	0.76	31.75	83.82	26.67	1
5	8.64	90.68	22.61	17.27	14.73	39.37	45.72	24.38	47.75	1
6	36.83	15.49	21.59	2.03	0.00	50.29	29.72	31.50	52.83	3
7	24.13	19.30	18.29	42.93	59.94	58.67	0.00	39.37	35.31	1
8	48.26	23.11	7.37	52.32	8.13	49.78	57.91	0.76	68.58	3
9	11.68	12.70	53.85	98.30	0.00	0.00	30.73	35.56	71.63	

	B	C	D
10			
11	t-Test: Paired Two Sample for Means		
12			
13		1	26
14	Mean	26.63371	12.48229
15	Variance	189.1916	120.6971
16	Observations	7	7
17	Pearson Correlation	-0.28227	
18	Hypothesized Mean Difference	0	
19	df	6	
20	t Stat	1.883399	
21	P(T<=t) one-tail	0.054321	
22	t Critical one-tail	1.943181	
23	P(T<=t) two-tail	0.108642	
24	t Critical two-tail	2.446914	
25			

Figure 157. Results of the paired t-test analysis of the precipitation data.

The procedures for conducting a non-paired two sample t-test are nearly identical. The principal difference is in the two sample sets. Whereas one would have sample groups of equal sizes for the paired test, one can compare unpaired sample groups of different sizes in the non-paired two sample t-test. To conduct this test, select ***<Data Analysis>*** from the <Tools> menu, and then select ***<t-test: Two-Sample Assuming Equal Variances>*** or ***<t-test: Two-Sample Assuming Unequal Variances>*** depending on which assumptions are applicable for your test.

11.12.4.3 One-way Analysis of Variance (ANOVA)

While t-tests are valuable for simple comparisons of two groups of data, they are prone to experiment-wise errors when applied to repeated measures. Analysis of variance (ANOVA) is a very powerful and appropriate tool when conducting comparisons of multiple sets of data.

Again using the precipitation data, let us test to see if there are actually any weeks of the year where precipitation is statistically greater than or less than other weeks.

Figure 158 shows the dialog box and results from the ANOVA. The steps are relatively straightforward. As in the paired t-test, the comparison groups are organized by columns. We specified the 52 columns corresponding to each week of the year, and then indicated that the first row of data contains column header/label information. We specified an alpha level of .05, and asked for the data to be exported to cell **A11**. After clicking on the "OK" button, the results were printed to the worksheet.

The results indicate that the probability is approximately 0.74 that the differences among the periods examined are due to chance alone. Two possible conclusions are: (1) mean weekly precipitation levels throughout the year since 1990 have been relatively even from week to week, or (2) the sample size of seven years (1990-1996) is too small and/or variable to detect any differences that do exist.

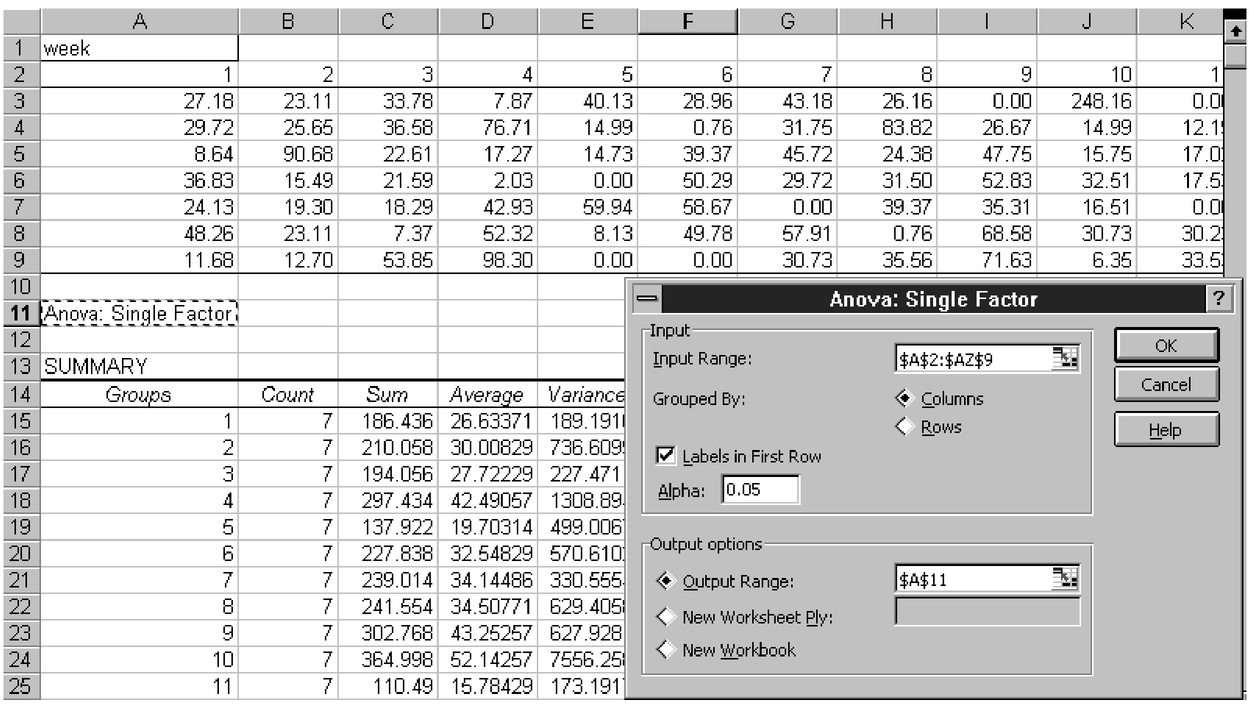


Figure 158. Example of a Single Factor Analysis of Variance (ANOVA) on the precipitation data.

11.12.4.4 Correlations

One other practical tool for statistical analysis is correlation analysis. Excel will calculate the correlation between rows or columns of data, and report the results in a correlation matrix. For this section we will use a different example dataset, as follows:

Table 70. Example dataset for the correlation analysis.

One’s	1	1	1	1	1
Two’s	2	2	2	2	2
Ascending	1	2	3	4	5
Descending	5	4	3	2	1
Random	0.509693235	0.677558127	0.235359559	0.147237963	0.904992965

The correlation analysis is set up in a nearly identical fashion as was done for the previous examples. Select “Correlation” from the list of Data Analysis tools accessed from the “Tools” menu. In this case the data are organized by rows, so we specified the “Grouped by rows” check box. Note that the 5th row contains a series of random numbers generated in Excel using the Random() function. We identified that the first column contains header/label information, and then specified cell A8 for the results, Clicking on “OK” yielded the results in Figure 159.

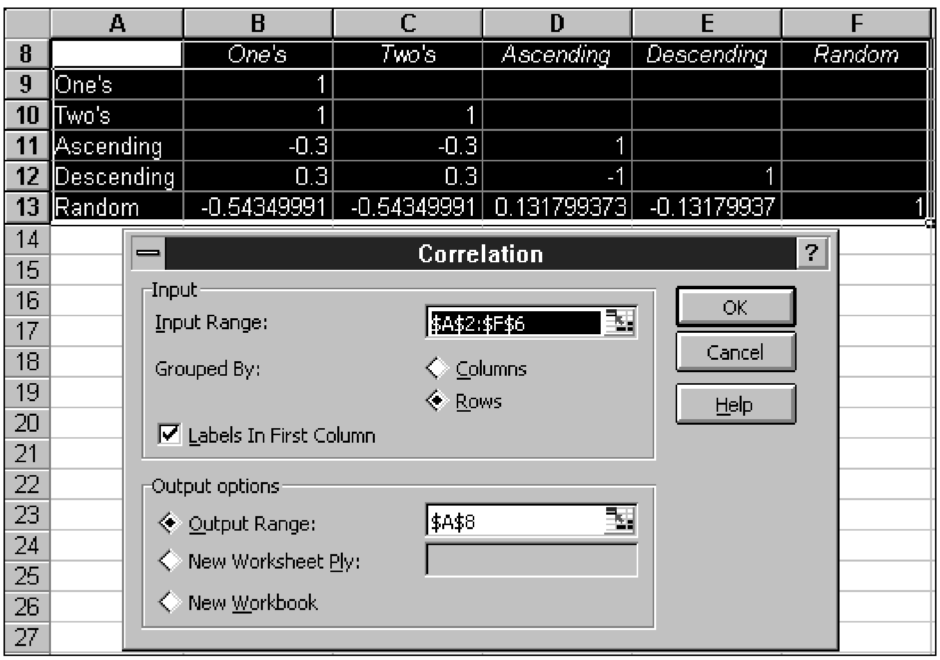


Figure 159. Example of a Correlation analysis in Excel.

The results of the analysis suggest that the ones and twos are highly correlated (correlation = 1), that the Ascending and Descending columns are highly anti-correlated (correlation = -1), and that the correlations between the other pairs are relatively uncorrelated.

11.13 Guidelines for Reporting Monitoring Results

11.13.1 Purpose and Types of Reports

The purpose of a report is to present information and facts, examine relationships, and present conclusions based on the information analyzed. A report provides readers with background information and an understanding of the state of the natural resources on an installation. In some cases, this could be the first comprehensive document describing or summarizing an installation's natural resources. Some specific installation questions cannot be directly address by the data set or other available resources. However, working with the data will help recognize additional data needs. Conclusions made should deduced from the results and data presented in the report.

The types of reports that precede the one to be written may define the level of detail. An initial report may contain much more detail than subsequent reports. Once a foundation is established, only new information should be addressed. The intent is to refresh memories and to direct interested parties to earlier reports for more detailed information. An initial report may inform the geologist who finds the occurrence of an endangered plant on a specific geological formation interesting, or the trainer who is curious about expanding training activities into an under-utilized area. If trend analysis is important, then it is essential to present results over the available time period.

A report addresses a problem or question in specific terms. Essential facts are classified and organized with an emphasis on processes, causes, and results. The facts are evaluated and interpreted. Some reports may emphasize recommendations which serve as the basis for future action. Recommendations should exclude personal opinion, interest, and bias (Jones 1976).

In many situations, a report is used as a tool to help managers and funding agencies assess the success of a project or program (Pneena 1986). The type of question and the audience defines a report's structure and content. Typically, a report that will be reviewed and used by colleagues is more detailed than one required by those at higher organizational levels. Regardless of the depth of analysis and presentation, all statements must meet scientific evaluation standards.

Report writing requires a number of tasks that contribute to the overall product. For example, the following tasks are typically associated with producing a comprehensive monitoring report, addressing a variety of issues and including both qualitative and quantitative data summaries:

Assemble Information: this task may require inventories of available background information including descriptive (i.e., plans, reports) and spatial (i.e., map and GIS) data. A literature search using library and installation documents is essential to the validity of the report by providing additional substance and building on the work of others. A literature search should provide important background and reference information regarding ecology, monitoring approaches, and management issues.

Data Preparation: requires the assembly, organization, and evaluation of existing data to be analyzed in the report. Missing or invalid data should be found or corrected, respectively. Data may have to be reformatted depending on the analysis tools. This is sometimes a very time-consuming effort, depending on quality control and data management efforts up to that point. Report preparation and writing requires the database be complete, organized, and in condition for general use.

Data Summary and Statistical Analysis: Once the objectives of the report are determined, data can be summarized and analyzed. Analysis typically involves extracting summaries from raw data and subsequent analysis.

Prepare Graphics and Write: Once summaries are generated, graphics can be developed for the report. Graphics are often prepared as a framework for the presentation and discussion of results.

Submit to Others for Review and Perform Final Edits: The draft report should be reviewed by both members of the intended audience and others who have a good understanding of the subject matter. Once edits are completed, the report is ready for reproduction, binding, and distribution.

11.13.2 Generic Report Organization

Reports generally follow scientific writing protocols and include an introduction, methods and materials, results and discussion, conclusions, and recommendations. Report writing requires both structured analysis and creativity.

11.13.2.1 Preliminary Sections

Title page, table of contents, list of tables, list of figures, and funding source make up the preliminary pages of a report. Additional pages may include acknowledgments, executive summary, abstract, or preface. These pages are numbered with lower case Roman numerals. These initial pages allow the reader to find specific information and quickly achieve a sense for the organization, rationale, and findings of the report.

The title page includes the title of the report, authorship and affiliation, for whom the report was prepared, and the date. The title should be concise and informative. Authorship is typically given to those individuals who have substantially contributed to the report. Individuals who have advised or given technical assistance as part of their normal duties are not included as authors. All authors should review and approve the final draft (O'Connor and Woodford 1975, National Bureau of Standards 1980).

The table of contents typically includes primary and secondary section headings. Additional levels of organization can be included if so desired. Descriptive headings will lead readers to sections of interest. A list of figures and tables should follow the section locations. Concise and informative titles to figures and tables are helpful to readers.

The executive summary is a condensed version of the report. Limited to one or two pages, an executive summary presents the rationale for the report, the findings, conclusions, and recommendations in a non technical way (Shelton 1994). An abstract is similar to an executive summary but is generally shorter, often a single paragraph. Acknowledgments recognize individuals or groups who have made a significant contribution to the report, but who cannot be regarded as authors.

11.13.2.2 Introduction

The introduction sets the stage for the report. The background, justification, and the scope of the project or program are described. The project goals and objectives are presented in a clear, concise manner. The introduction may include a general description of the site location and an installation's mission. Background information relevant to the ecology and history of the project area aids in justifying methods and objectives. Land uses unique to the installation may be described, especially if they affect the interpretation of results.

11.13.2.3 Study Area or Site Description

A summary of an installation's natural resources should include geologic development and features, soils, climate, vegetation, wildlife, physiography, hydrography, and special concerns. Any attribute reviewed should aid the project information that will be presented later in the report.

Natural Resources -- The natural resources are the setting upon which an installation's mission(s) takes place. Often mission is defined by the resources available. How these resources are used and preserved are an important part of mission continuation. A description of the natural resources provides a framework to anchor the field data.

Geological Development and Features -- The geology of an area affects the types of soils present as well as the associated vegetation. A description of the geology can outline a number of physical limitations to training. Geology can also help explain why certain areas are more heavily used, and why other sites should not be used.

Soils -- An installation's soils are related to geology, landform, relief, climate, and the vegetation (Cochran 1992). The information identifies the potential constraints to training, vegetation patterns, and the likelihood of erosion problems. Not all installations have specific soil information available. For installations with completed soil surveys, the Natural Resources Conservation Service (NRCS) can provide needed information. In addition, the NRCS can provide the R-value used in calculating soil erosion potential with the Universal Soil Loss Equation.

Climate -- Many installations have weather stations on site. Often these stations are at airfields. Data are available from the National Climatic Data Center, Asheville, North Carolina, for established stations. These data are also available on CDROM from EarthInfo, Inc, Boulder, Colorado (http://www.csn.net/~jacke/index.html). Compact disks (CDs) containing these data may be available from university libraries. Some data are available on the world wide web. For example, see: On Line Climate Data page; http://www.ncdc.noaa.gov/ol/climate/climatedata.html.

Vegetation -- Putting the vegetation into a historical framework helps readers understand the associations present and responses to natural and human-induced events. Severe disturbances may simplify or add to the vegetative complexity. In a historical context, the sensitivity, resistance, and resilience of the vegetation may become more apparent. This information may help in planning prescribed burns, forestry practices, or agricultural leases.

Wildlife -- As with vegetation, a brief background of the wildlife present is helpful to the reader.

Pysiography -- Landform, topographic position, and aspect can be important determinants of plant communities. This information may be derived in part from elevation layers using a GIS. Field data collection and soil surveys also provide information.

Hydrography -- Streams and water body locations are available from digital and paper maps. Stream flow information for gauges are usually maintained by universities and/or state agencies, and is often available via the world wide web.

Areas of Special Interest or Concern -- Areas of special interest may be descriptions or locations of species of concern, natural features or plant communities, wetlands, soils, etc. A brief description of the areas, their importance, and ongoing measures for protection help the reader understand the natural resources of an installation.

11.13.2.4 Methods

The methodology of a project should be explained with enough detail for the project to be repeated, achieving similar results. Detailed methodologies can be presented in other documents such as a monitoring protocol. Any modifications or methods unique to the project need to be detailed. General treatments and sample size(s) must be provided, as well as the duration and time of fieldwork. Statistical analyses and justifications can be addressed in detail in this section and then mentioned in the results.

11.13.2.5 Results and Discussion

The results and the discussion can be either one or two sections. Placing them together is easier to write and easier on the reader, especially if the study is complex. If the two sections are separate, be sure not to discuss results in the results section and to address all of the results in the discussion section. Make the results section comprehensible and coherent on its own. Describe the purpose, the significance, and the relevance of the information, but do not discuss the results extensively. Refer to tables and figures to illustrate the findings and support conclusions. Excessive description of data already presented in graphics should be avoided. However, no table or figure should be included that is not directly cited and relevant to the discussion. Descriptions of and references to tables and figures should be straightforward and explicit.

Develop the discussion in the same order as the results were presented. The discussion is an elaboration and an assessment of the results section. The results are related to previous studies and the implications of the results are discussed. Do not conceal negative results and discrepancies. Instead, try to explain, or admit your inability to do so (O'Connor and Woodford 1975).

11.13.2.6 Conclusions and Recommendations

The conclusions tie the objective(s) to the results and the discussion. The emphasis is on what was found in light of the stated objectives of the report. The conclusions re-address the important findings of the project. If someone were to only read the introduction and the conclusion, they should have a good idea of the contents of the report. Recommendations are based on the technical evidence and the author's professional expertise (Shelton 1994). When data and expertise do not answer the objectives of a project, recommendations should address alternative methods or approaches.

11.13.2.7 Literature Cited and Bibliographic References

If a report is going to be published, all published works cited must be referenced. Unpublished works, obscure documents, and personal communications are not included in the literature cited, but should be referenced in the text or placed in a footnote if more detailed information is necessary. The format of the Literature Cited section should be consistent and have a logical organization.

11.13.3 Style and Format

All communication is imperfect, because the ability to understand information depends on both the sender and the receiver (Pneena 1986). Style is a subtle method of encouraging someone to read the written word. Style includes everything from page layout to grammar to choice of words. Style is largely a personal characteristic but authors should always strive for clarity, conciseness, and consistency.

> *Vigorous writing is concise. A sentence should contain no unnecessary wrods, a paragraph no unnecessary sentences, for the same reason that a drawing should contain no unnecessary lines and a machine no unnecessary parts…* -- (Strunk and White 1979)

The format of a document is an invitation to read the document or put it down. Pick a font, type size, and line spacing that makes reading easy. Use descriptive headings to help readers locate specific topics and to break up the page. Illustrations provide information in an alternative format and give the reader a momentary diversion. Bulleted items alter the overall look to a page and provide a change in rhythm. Do not, however, add so many distractions and increase margins and line spacing to make the reader wonder why so much paper is being used. Additional writing references include Sabin (1993) and Style Manual Committee (1994).

11.13.3.1 Tips for Effective Writing

Effective writing is a skill learned over time, which comes naturally to some, but is laborious to most. Some writing critiques and editorial revisions are based on style differences and not grammatical problems. Some errors seen by others would be evident to the writer if there was time to put the document aside for awhile. Pneena (1986) presents some simple writing techniques to keep in mind while writing and proof reading a report:

1. Avoid long, convoluted sentences and paragraphs.

2. Avoid jargon.

3. Limit the use of prepositions - the number of prepositional phrases in a sentence makes reading and understanding laborious.

4. Whenever possible, use precise writing in favor of comfortable writing. Examples include:

COMFORTABLE WRITING	PRECISE WRITING
was low **in** frequency	less frequent
was **of** greater importance	was more important
in order to	to
the preparation **of** reports	preparing reports
the targeting **of** erosion	targeting erosion
to be used **in** place of	to replace
are **of** importance	are important

5. Limit the use of the word 'and' to join phrases. Instead:
   - Use short sentences.
   - Use other connectives (e.g., *thus, often, in addition*).
   - Connected items must parallel each other (i.e., the same structural or grammatical form for all parts of a series -- *preparing documentation, reporting findings, and addressing goals*).

6. Limit clutter words and crutch phrases (e.g., there are, it is apparent that, it is important to note, etc.).

7. Limit repeating expressions (e.g., ***Invasive species*** *abundance in Training Area 2A increased by 12% , which was a much larger increase in* ***invasive species*** *abundance compared to Training Area 2B.)*

8. Limit unnecessary adjectives and adverbs (e.g., it seems, likelihood, sufficiently, frequently, etc.).

9. Use ordinary words.

10. Limit verbs such as *is* and *occurred*.

11. Conduct *which* hunts. *Which* is used to introduce nonessential clauses: "Training intensity increased from 1995 to 1998, *which was the consequence of mission change*". T*hat* ordinarily introduces essential clauses: "The report *that we prepared for the Colonel* should be of help."

12. Follow *which* hunts by searches for the words *that, it,* and *of.* Sometimes these are the best words, but often they are not.

13. Use the active verb tense rather than the passive. Using the passive verb tense is common and accepted in scientific writing, but should be minimized.

14. Put related but non-essential information into an appendix. Information contained in appendices should be cited in the text; otherwise, another document may be a more appropriate place for the information. Do not put copious amounts of raw data in an appendix unless it serves a useful purpose.

11.13.4 Tables

Every table must have a purpose and convey a message. A table should be able to stand alone from the text. The table title should be descriptive. If a number of tables contain similar information, the legend of the first should be inclusive of all necessary information. In subsequent tables, the previous table can be cited for the specifics.

A table's format needs to be logical. If the amount of data is voluminous, break into a summary table for the text and place the whole table in an appendix. Put control or base values near the beginning of the table. Columns with comparative data should be next to each other.

The number of significant figures (i.e., decimal places) should be consistent and indicative of the level of precision used in measurement. When possible align numbers using decimal points. The number of samples, the standard error or standard deviation of the mean, the probability, and the type of statistical analysis should be stated.

Table 15A. Mean canopy intercepts +/- their means in the South Camp at Camp USA, 1997 and 1999. Probabilities based on single-factor ANOVA.

Training Areas	Years				
	1997	*n**	1999	*n*	Probability
TA 6	157.1 +/- 10.23	21	101.1 +/- 10.34	23	<0.01
TA 7	152.0 +/- 16.08	20	123.3 +/- 14.32	26	0.19
TA 8	245.1 +/- 21.31	15	175.7 +/- 15.74	15	0.01
TA 9	320.8 +/- 24.49	13	255.8 +/- 24.78	13	0.07
TA 10	334.2 +/- 86.60	8	296.2 +/- 76.40	8	0.75
TA 11	433.8 +/- 71.62	10	340.4 +/- 61.55	10	0.34

* The letter *n* indicates the number of samples.

- ✓ Able to stand alone
- ✓ Format logical
- ✓ Limited amount of information
- ✓ Note sample size
- ✓ Measure of statistical variability shown
- ✓ Statistical test noted
- ✓ Terms explained

Figure 160. Example of tabular data that includes essential components.

11.13.5 Graphics

A graphic, like a table, needs to be interpreted independent from the text. Most graphics are titled as Figures in a report. Types of graphics include maps; histograms, line graphs, pie charts, and other representations of qualitative or quantitative information; flow charts; organizational charts, illustrations, and photographs. The title or figure caption should be informative and contain information to explain the graphic. If a number of similar graphics occur together, the legend of the first graphic should be complete to avoid unnecessary replication. Subsequent legends can then refer to the earlier figure for specific information. Examples of properly labeled and captioned graphics are presented in Figure 161.

All axes must be labeled and measurement units displayed if appropriate. Standard errors or standard deviations of the mean, sample size, and the type of statistical test used should be included. Symbols and lettering must be defined. Also, do not extrapolate beyond sample data without an explanation or a caution to readers.

Although color figures can add to the cost of report reproduction, they can significantly enhance the appearance of results. If color figures are used, choose colors that are pleasing and reproduce well in black and white. Size figures so the information is clear and easily discerned. Most figures can be presented in the text instead of using an entire page.

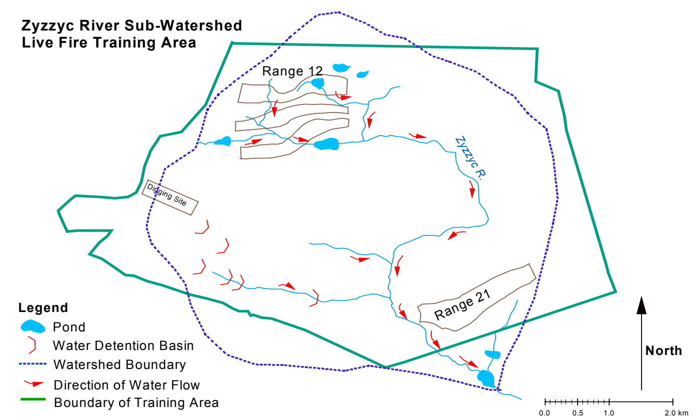


Figure 3. Water flow in the Zyzzyc River Sub-Watershed located in the Live Fire Training Area of Camp USA.

- ✓ Title describes graphic
- ✓ Legend includes all boundaries and symbols
- ✓ The graphic can stand alone
- ✓ The graphic is understandable in black and white
- ✓ Map figures should include a North arrow and scale bar

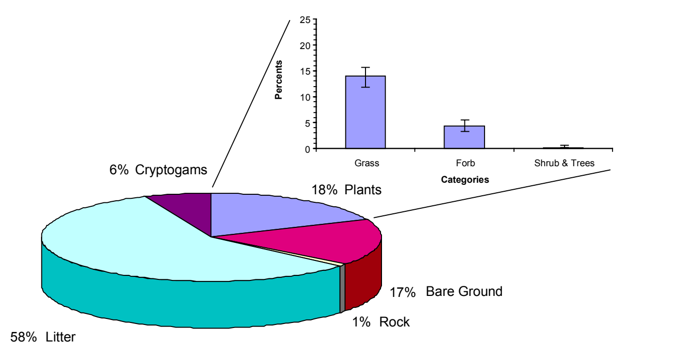


Figure 13. Ground cover by category on 110 plots at Camp USA. Means and their standard errors shown for plant cover types.

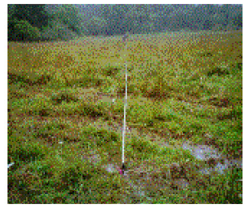
- ✓ Title describes graphic
- ✓ All symbols are identified
- ✓ The colors are distinguishable in black and white
- ✓ The title legend includes the type of statistical test used

Figure 161. Example of graphics showing necessary components.

11.13.6 Abbreviated Format

As stated above, professional colleagues tend to expect more detail and a higher level of reporting compared to inexperienced or non-technical staff. A comprehensive report, reviewing a number of years of data, can consist of over 100 pages of text, and with appendices, a report can approach 150 pages. While the complexity of a report is necessary, a brief review of the contents is often appreciated. One method is to develop a computer presentation. The objectives as they pertain to a specific audience can be highlighted. The methods, data, results, discussion, and conclusions are developed for the intended audience, and illustrated as bulleted items. Photographs illustrating the data, rather than tables and charts provide a more dynamic document and a document supported by scientific protocols. Results can be presented in an abbreviated format (Figure 162) or condensed to the level of information common to presentation slides (Figure 163).

Disturbance

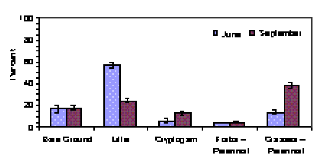


Plot 303 was used as an assembly area. Note the pooling of water. The terrain is level enough in many areas to prevent water flow off-site. However, in some locations water was noted running through the grass to lower points. In these cases the vegetation and litter acted as filters of sediment.

Rainfall during September was atypically high, nearly equaling the average rainfall for an entire year.

20

Ground Cover



Five ground cover components were measured -- bare ground, gravel, litter, basal plant interceptions, and cryptogams.

Bare ground averaged 17% in both June and September with no statistically significant difference between the means (P = 0.83).

Litter decreased 57% by the September survey. The decrease was significant (P < 0.05) and due to the mechanical and biological breakdown.

Cryptogams doubled between the two surveys (6.3% – June; 12.7% – September). The increase was statistically significant (P < 0.05). The increase was due to growth of the cryptogams and the reduction of vascular plant cover, making the soil's surface easier to access and see.

Perennial forbs increased from 4% in June to nearly 5% in September (P = 0.34).

Perennial grasses increased nearly two-fold by September. The increase was statistically significant (P < 0.05). The increase in grass cover was the difference between hitting a plant at its center vs. recording a prostrate portion of the plant touching the ground, which was more common later in the season.

14

Figure 162. Examples of abbreviated reporting approach.

Figure 163. Example of information slide prepared for oral presentation.

11.13.7 Additional Recommendations

Reporting of monitoring results should be done in a timely and efficient manner. Data should be converted to electronic format, if appropriate, summarized, and evaluated before the beginning of the next data collection cycle. To ensure continued program support, monitoring programs must generate reports that are useful, address specific management concerns or issues, and widely applicable. The precision of the data should be known and specifically stated in summaries and reports. Lastly, reports should be prepared and distributed on a regular basis using a format that is straightforward and appropriate to the user community, including range operations personnel/military trainers, land managers, and public land agencies (e.g., where BLM, National Forest, and State lands are used for training).

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11.15 Appendix Statistical Reference Tables

Table 71 Critical values of the two tailed Student's t-distribution

Table 72 Critical values for correlation coefficients

Table 73 Binomial (percentage) confidence limits table

Table 74 Critical values of the chi-square distribution

Table 71. Critical values of the two-tailed Student's t-distribution. Reprinted with permission from Rohlf and Sokal, Table 12.

To look up the critical values of t for a given number of degrees of freedom, look up v = n-1 df in the left column of the table and read off the desired values of t in that row. If a one-tailed test is desired, the probabilities at the head of the table must be halved. For example, for a one-tailed test with 4 df, the critical value of t = 3.474 delimits 0.01 of the area of the curve.

$\nu \backslash \alpha$	0.9	0.5	0.4	0.2	0.1	0.05	0.02	0.01	0.001	α / ν
1	.158	1.000	1.376	3.078	6.314	12.706	31.821	63.657	636.619	1
2	.142	.816	1.061	1.886	2.920	4.303	6.965	9.925	31.598	2
3	.137	.765	.978	1.638	2.353	3.182	4.541	5.841	12.924	3
4	.134	.741	.941	1.533	2.132	2.776	3.747	4.604	8.610	4
5	.132	.727	.920	1.476	2.015	2.571	3.365	4.032	6.869	5
6	.131	.718	.906	1.440	1.943	2.447	3.143	3.707	5.959	6
7	.130	.711	.896	1.415	1.895	2.365	2.998	3.499	5.408	7
8	.130	.706	.889	1.397	1.860	2.306	2.896	3.355	5.041	8
9	.129	.703	.883	1.383	1.833	2.262	2.821	3.250	4.781	9
10	.129	.700	.879	1.372	1.812	2.228	2.764	3.169	4.587	10
11	.129	.697	.876	1.363	1.796	2.201	2.718	3.106	4.437	11
12	.128	.695	.873	1.356	1.782	2.179	2.681	3.055	4.318	12
13	.128	.694	.870	1.350	1.771	2.160	2.650	3.012	4.221	13
14	.128	.692	.868	1.345	1.761	2.145	2.624	2.977	4.140	14
15	.128	.691	.866	1.341	1.753	2.131	2.602	2.947	4.073	15
16	.128	.690	.865	1.337	1.746	2.120	2.583	2.921	4.015	16
17	.128	.689	.863	1.333	1.740	2.110	2.567	2.898	3.965	17
18	.127	.688	.862	1.330	1.734	2.101	2.552	2.878	3.922	18
19	.127	.688	.861	1.328	1.729	2.093	2.539	2.861	3.883	19
20	.127	.687	.860	1.325	1.725	2.086	2.528	2.845	3.850	20
21	.127	.686	.859	1.323	1.721	2.080	2.518	2.831	3.819	21
22	.127	.686	.858	1.321	1.717	2.074	2.508	2.819	3.792	22
23	.127	.685	.858	1.319	1.714	2.069	2.500	2.807	3.767	23
24	.127	.685	.857	1.318	1.711	2.064	2.492	2.797	3.745	24
25	.127	.684	.856	1.316	1.708	2.060	2.485	2.787	3.725	25
26	.127	.684	.856	1.315	1.706	2.056	2.479	2.779	3.707	26
27	.127	.684	.855	1.314	1.703	2.052	2.473	2.771	3.690	27
28	.127	.683	.855	1.313	1.701	2.048	2.467	2.763	3.674	28
29	.127	.683	.854	1.311	1.699	2.045	2.462	2.756	3.659	29
30	.127	.683	.854	1.310	1.697	2.042	2.457	2.750	3.646	30
40	.126	.681	.851	1.303	1.684	2.021	2.423	2.704	3.551	40
60	.126	.679	.848	1.296	1.671	2.000	2.390	2.660	3.460	60
120	.126	.677	.845	1.289	1.658	1.980	2.358	2.617	3.373	120
∞	.126	.674	.842	1.282	1.645	1.960	2.326	2.576	3.291	∞

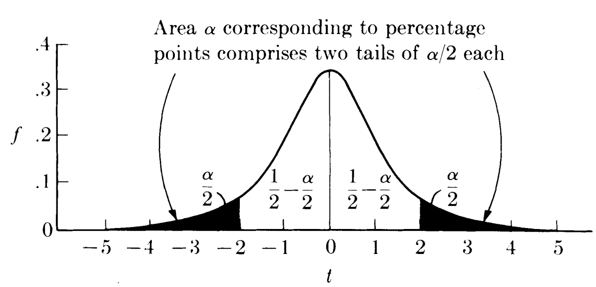

Table 72. Critical values for (product moment) correlation coefficients. Reprinted with permission from Sokal and Rohlf 1981, Table 25.

To test the significance of a correlation coefficient, the sample size *n* upon which it is based must be known. Enter the table for v = n-2 degrees of freedom and consult the first column of values headed "number of independent variables".

		k Number of independent variables			
v	α	1	2	3	4
1	.05	.997	.999	.999	.999
	.01	1.000	1.000	1.000	1.000
2	.05	.950	.975	.983	.987
	.01	.990	.995	.997	.998
3	.05	.878	.930	.950	.961
	.01	.959	.976	.983	.987
4	.05	.811	.881	.912	.930
	.01	.917	.949	.962	.970
5	.05	.754	.836	.874	.898
	.01	.874	.917	.937	.949
6	.05	.707	.795	.839	.867
	.01	.834	.886	.911	.927
7	.05	.666	.758	.807	.838
	.01	.798	.855	.885	.904
8	.05	.632	.726	.777	.811
	.01	.765	.827	.860	.882
9	.05	.602	.697	.750	.786
	.01	.735	.800	.836	.861
10	.05	.576	.671	.726	.763
	.01	.708	.776	.814	.840
11	.05	.553	.648	.703	.741
	.01	.684	.753	.793	.821
12	.05	.532	.627	.683	.722
	.01	.661	.732	.773	.802
13	.05	.514	.608	.664	.703
	.01	.641	.712	.755	.785
14	.05	.497	.590	.646	.686
	.01	.623	.694	.737	.768
15	.05	.482	.574	.630	.670
	.01	.606	.677	.721	.752
16	.05	.468	.559	.615	.655
	.01	.590	.662	.706	.738
17	.05	.456	.545	.601	.641
	.01	.575	.647	.691	.724
18	.05	.444	.532	.587	.628
	.01	.561	.633	.678	.710
19	.05	.433	.520	.575	.615
	.01	.549	.620	.665	.698
20	.05	.423	.509	.563	.604
	.01	.537	.608	.652	.685
21	.05	.413	.498	.522	.592
	.01	.526	.596	.641	.674
22	.05	.404	.488	.542	.582
	.01	.515	.585	.630	.663
23	.05	.396	.479	.532	.572
	.01	.505	.574	.619	.652
24	.05	.388	.470	.523	.562
	.01	.496	.565	.609	.642
25	.05	.381	.462	.514	.553
	.01	.487	.555	.600	.633
26	.05	.374	.454	.506	.545
	.01	.478	.546	.590	.624
27	.05	.367	.446	.498	.536
	.01	.470	.538	.582	.615
28	.05	.361	.439	.490	.529
	.01	.463	.530	.573	.606
29	.05	.355	.432	.482	.521
	.01	.456	.522	.565	.598
30	.05	.349	.426	.476	.514
	.01	.449	.514	.558	.591
35	.05	.325	.397	.445	.482
	.01	.418	.481	.523	.556
40	.05	.304	.373	.419	.455
	.01	.393	.454	.494	.526
45	.05	.288	.353	.397	.432
	.01	.372	.430	.470	.501
50	.05	.273	.336	.379	.412
	.01	.354	.410	.449	.479
60	.05	.250	.308	.348	.380
	.01	.325	.377	.414	.442
70	.05	.232	.286	.324	.354
	.01	.302	.351	.386	.413
80	.05	.217	.269	.304	.332
	.01	.283	.330	.362	.389
90	.05	.205	.254	.288	.315
	.01	.267	.312	.343	.368
100	.05	.195	.241	.274	.300
	.01	.254	.297	.327	.351
125	.05	.174	.216	.246	.269
	.01	.228	.266	.294	.316
150	.05	.159	.198	.225	.247
	.01	.208	.244	.270	.290
200	.05	.138	.172	.196	.215
	.01	.181	.212	.234	.253
300	.05	.113	.141	.160	.176
	.01	.148	.174	.192	.208
400	.05	.098	.122	.139	.153
	.01	.128	.151	.167	.180
500	.05	.088	.109	.124	.137
	.01	.115	.135	.150	.162
1,000	.05	.062	.077	.088	.097
	.01	.081	.096	.106	.115

Table 73. Confidence limits for percentages (for sample sizes up to n=30) based on the binomial distribution. Reprinted with permission from Sokal and Rohlf 1981, Table 23.

Y	Confidence coefficients	n = 5	10	15	20	25	30	Confidence coefficients	Y
0	95	0.00 - 45.07	0.00 - 25.89	0.00 - 18.10	0.00 - 13.91	0.00 - 11.29	0.00 - 9.50	95	0
		0.00	0.00	0.00	0.00	0.00	0.00		
	99	0.00 - 60.19	0.00 - 36.90	0.00 - 26.44	0.00 - 20.57	0.00 - 16.82	0.00 - 14.23	99	
1	95	0.51 - 71.60	0.25 - 44.50	0.17 - 32.00	0.13 - 24.85	0.10 - 20.36	0.08 - 17.23	95	1
		20.00	10.00	6.67	5.00	4.00	3.33		
	99	0.10 - 81.40	0.05 - 54.4	0.03 - 40.27	0.02 - 31.70	0.02 - 26.24	0.02 - 22.33	99	
2	95	5.28 - 85.34	2.52 - 55.60	1.66 - 40.49	1.24 - 31.70	0.98 - 26.05	0.82 - 22.09	95	2
		40.00	20.00	13.33	10.00	8.00	6.67		
	99	2.28 - 91.72	1.08 - 64.80	0.71 - 48.71	0.53 - 38.70	0.42 - 32.08	0.35 - 27.35	99	
3	95		6.67 - 65.2	4.33 - 48.07	3.21 - 37.93	2.55 - 31.24	2.11 - 26.53	95	3
			30.00	20.00	15.00	12.00	10.00		
	99		3.70 - 73.50	2.39 - 56.07	1.77 - 45.05	1.40 - 37.48	1.16 - 32.03	99	
4	95		12.20 - 73.80	7.80 - 55.14	5.75 - 43.65	4.55 - 36.10	3.77 - 30.74	95	4
			40.00	26.67	20.00	16.00	13.33		
	99		7.68 - 80.91	4.88 - 62.78	3.58 - 50.65	2.83 - 42.41	2.34 - 36.39	99	
5	95		18.70 - 81.30	11.85 - 61.62	8.68 - 49.13	6.84 - 40.72	5.64 - 34.74	95	5
			50.00	33.33	25.00	20.00	16.67		
	99		12.80 - 87.20	8.03 - 68.89	5.85 - 56.05	4.60 - 47.00	3.79 - 40.44	99	
6	95			16.33 - 67.74	11.90 - 54.30	9.35 - 45.14	7.70 - 38.56	95	6
				40.00	30.00	24.00	20.00		
	99			11.67 - 74.40	8.45 - 60.95	6.62 - 51.38	5.43 - 44.26	99	
7	95			21.29 - 73.38	15.38 - 59.20	12.06 - 49.38	9.92 - 42.29	95	7
				46.67	35.00	28.00	23.33		
	99			15.87 - 79.54	11.40 - 65.70	8.90 - 55.56	7.29 - 48.01	99	
8	95				19.10 - 63.95	14.96 - 53.50	12.29 - 45.89	95	8
					40.00	32.00	26.67		
	99				14.60 - 70.10	11.36 - 59.54	9.30 - 51.58	99	
9	95				23.05 - 68.48	17.97 - 57.48	14.73 - 49.40	95	9
					45.00	36.00	30.00		
	99				18.08 - 74.30	14.01 - 63.36	11.43 - 55.00	99	
10	95				27.20 - 72.80	21.12 - 61.32	17.29 - 52.80	95	10
					50.00	40.00	33.33		
	99				21.75 - 78.25	16.80 - 67.04	13.69 - 58.35	99	
11	95					24.41 - 65.06	19.93 - 56.13	95	11
						44.00	36.67		
	99					19.75 - 70.55	16.06 - 61.57	99	
12	95					27.81 - 68.69	22.66 - 59.39	95	12
						48.00	40.00		
	99					22.84 - 73.93	18.50 - 64.69	99	
13	95						25.46 - 62.56	95	13
							43.33		
	99						21.07 - 67.72	99	
14	95						28.35 - 65.66	95	14
							46.67		
	99						23.73 - 70.66	99	
15	95						31.30 - 68.70	95	15
							50.00		
	99						26.47 - 73.53	99	

Table 73 Continued. Confidence limits for percentages based on the binomial distribution, for larger sample sizes (n=50, 100, 200, 500, and 1000). Reprinted with permission from Sokal and Rohlf 1981, Table 23.

		n				
%	**Confidence coefficients**	**50**	**100**	**200**	**500**	**1000**
0	95	.00- 5.82	.00- 2.95	.00- 1.49	.00- 0.60	.00- 0.30
	99	.00- 8.80	.00- 4.50	.00- 2.28	.00- 0.92	.00- 0.46
1	95	(.02- 8.88)	.02- 5.45	.12- 3.57	.32- 2.32	.48- 1.83
	99	(.00-12.02)	.00- 7.21	.05- 4.55	.22- 2.80	.37- 2.13
2	95	.05-10.66	.24- 7.04	.55- 5.04	1.06- 3.56	1.29- 3.01
	99	.01-13.98	.10- 8.94	.34- 6.17	.87- 4.12	1.13- 3.36
3	95	(.27-12.19)	.62- 8.53	1.11- 6.42	1.79- 4.81	2.11- 4.19
	99	(.16-15.60)	.34-10.57	.78- 7.65	1.52- 5.44	1.88- 4.59
4	95	.49-13.72	1.10- 9.93	1.74- 7.73	2.53- 6.05	2.92- 5.36
	99	.21-17.21	.68-12.08	1.31- 9.05	2.17- 6.75	2.64- 5.82
5	95	(.88-15.14)	1.64-11.29	2.43- 9.00	3.26- 7.29	3.73- 6.54
	99	(.45-18.76)	1.10-13.53	1.89-10.40	2.83- 8.07	3.39- 7.05
6	95	1.26-16.57	2.24-12.60	3.18-10.21	4.11- 8.43	4.63- 7.64
	99	.69-20.32	1.56-14.93	2.57-11.66	3.63- 9.24	4.25- 8.18
7	95	(1.74-17.91)	2.86-13.90	3.88-11.47	4.96- 9.56	5.52- 8.73
	99	(1.04-21.72)	2.08-16.28	3.17-12.99	4.43-10.42	5.12- 9.31
8	95	1.38-23.13	2.63-17.61	3.93-14.18	5.23-11.60	5.98-10.43
	99	2.23-19.25	3.51-15.16	4.70-12.61	5.81-10.70	6.42- 9.83
9	95	(2.78-20.54)	4.20-16.40	5.46-13.82	6.66-11.83	7.32-10.93
	99	(1.80-24.46)	3.21-18.92	4.61-15.44	6.04-12.77	6.84-11.56
10	95	3.32-21.82	4.90-17.62	6.22-15.02	7.51-12.97	8.21-12.03
	99	2.22-25.80	3.82-20.20	5.29-16.70	6.84-13.95	7.70-12.69
11	95	(3.93-23.06)	5.65-18.80	7.05-16.16	8.41-14.06	9.14-13.10
	99	(2.70-27.11)	4.48-21.42	6.06-17.87	7.70-15.07	8.60-13.78
12	95	4.54-24.31	6.40-19.98	7.87-17.30	9.30-15.16	10.06-14.16
	99	3.18-28.42	5.15-22.65	6.83-19.05	8.56-16.19	9.51-14.86
13	95	(5.18-27.03)	7.11-21.20	8.70-18.44	10.20-16.25	10.99-15.23
	99	(3.72-29.67)	5.77-23.92	7.60-20.23	9.42-17.31	10.41-15.95
14	95	5.82-26.75	7.87-22.37	9.53-19.58	11.09-17.34	11.92-16.30
	99	4.25-30.92	6.46-25.13	8.38-21.40	10.28-18.43	11.31-17.04
15	95	(6.50-27.94)	8.64-23.53	10.36-20.72	11.98-18.44	12.84-17.37
	99	(4.82-32.14)	7.15-26.33	9.15-22.58	11.14-19.55	12.21-18.13

Table 73 Continued.

%	Confidence coefficients	n = 50	100	200	500	1000
16	95	7.17-29.12	9.45-24.66	11.22-21.82	12.90-19.50	13.79-18.42
	99	5.40-33.36	7.89-27.49	9.97-23.71	12.03-20.63	13.14-19.19
17	95	(7.88-30.28)	10.25-25.79	12.09-22.92	13.82-20.57	14.73-19.47
	99	(6.00-34.54)	8.63-28.65	10.79-24.84	12.92-21.72	14.07-20.25
18	95	8.58-31.44	11.06-26.92	12.96-24.02	14.74-21.64	15.67-20.52
	99	6.60-35.73	9.37-29.80	11.61-25.96	13.81-22.81	14.99-21.32
19	95	(9.31-32.58)	11.86-28.06	13.82-25.12	15.66-22.71	16.62-21.57
	99	(7.23-36.88)	10.10-30.96	12.43-27.09	14.71-23.90	15.92-22.38
20	95	10.04-33.72	12.66-29.19	14.69-26.22	16.58-23.78	17.56-22.62
	99	7.86-38.04	10.84-32.12	13.26-28.22	15.60-24.99	16.84-23.45
21	95	(10.79-34.84)	13.51-30.28	15.58-27.30	17.52-24.83	18.52-23.65
	99	(8.53-39.18)	11.63-33.24	14.11-29.31	16.51-26.05	17.78-24.50
22	95	11.54-35.95	14.35-31.37	16.48-28.37	18.45-25.88	19.47-24.69
	99	9.20-40.32	12.41-34.35	14.97-30.40	17.43-27.12	18.72-25.55
23	95	(12.30-37.06)	15.19-32.47	17.37-29.45	19.39-26.93	20.43-25.73
	99	(9.88-41.44)	13.60-34.82	15.83-31.50	18.34-28.18	19.67-26.59
24	95	13.07-38.17	16.03-33.56	18.27-30.52	20.33-27.99	21.39-26.77
	99	10.56-42.56	13.98-36.57	16.68-32.59	19.26-29.25	20.61-27.64
25	95	(13.84-39.27)	16.88-34.66	19.16-31.60	21.26-29.04	22.34-27.81
	99	(11.25-43.65)	14.77-37.69	17.54-33.68	20.17-30.31	21.55-28.69
26	95	14.63-40.34	17.75-35.72	20.08-32.65	22.21-30.08	23.31-28.83
	99	11.98-44.73	15.59-38.76	18.43-34.75	21.10-31.36	22.50-29.73
27	95	(15.45-41.40)	18.62-36.79	20.99-33.70	23.16-31.11	24.27-29.86
	99	(12.71-45.79)	16.42-39.84	19.31-35.81	22.04-32.41	23.46-30.76
28	95	16.23-42.48	19.50-37.85	21.91-34.76	24.11-32.15	25.24-30.89
	99	13.42-46.88	17.25-40.91	20.20-36.88	22.97-33.46	24.41-31.80
29	95	(17.06-43.54)	20.37-38.92	22.82-35.81	25.06-33.19	26.21-31.92
	99	(14.18-47.92)	18.07-41.99	21.08-37.94	23.90-34.51	25.37-32.84
30	95	17.87-44.61	21.24-39.98	23.74-36.87	26.01-34.23	27.17-32.95
	99	14.91-48.99	18.90-43.06	21.97-39.01	24.83-35.55	26.32-33.87

Table 73 Continued. Large sample sizes (31%-50%).

%	Confidence coefficients	n 50	100	200	500	1000
31	95	(18.71-45.65)	22.14-41.02	24.67-37.90	26.97-35.25	28.15-33.97
	99	(15.68-50.02)	19.76-44.11	22.88-40.05	25.78-36.59	27.29-34.90
32	95	19.55-46.68	23.04-42.06	25.61-38.94	27.93-36.28	29.12-34.99
	99	16.46-51.05	20.61-45.15	23.79-41.09	26.73-37.62	28.25-35.92
33	95	(20.38-47.72)	23.93-43.10	26.54-39.97	28.90-37.31	30.09-36.01
	99	(17.23-52.08)	21.47-46.19	24.69-42.13	27.68-38.65	29.22-36.95
34	95	21.22-48.76	24.83-44.15	27.47-41.01	29.86-38.33	31.07-37.03
	99	18.01-53.11	22.33-47.24	25.60-43.18	28.62-39.69	30.18-37.97
35	95	(22.06-49.80)	25.73-45.19	28.41-42.04	30.82-39.36	32.04-38.05
	99	(18.78-54.14)	23.19-48.28	26.51-44.22	29.57-40.72	31.14-39.00
36	95	22.93-50.80	26.65-46.20	29.36-43.06	31.79-40.38	33.02-39.06
	99	19.60-55.13	24.08-49.30	27.44-45.24	30.53-41.74	32.12-40.02
37	95	(23.80-51.81)	27.57-47.22	30.31-44.08	32.76-41.39	34.00-40.07
	99	(20.42-56.12)	24.96-50.31	28.37-46.26	31.49-42.76	33.09-41.03
38	95	24.67-52.81	28.49-48.24	31.25-45.10	33.73-42.41	34.98-41.09
	99	21.23-57.10	25.85-51.32	29.30-47.29	32.45-43.78	34.07-42.05
39	95	(25.54-53.82)	29.41-49.26	32.20-46.12	34.70-43.43	35.97-42.10
	99	(22.05-58.09)	26.74-52.34	30.23-48.31	33.42-44.80	35.04-43.06
40	95	26.41-54.82	30.33-50.28	33.15-47.14	35.68-44.44	36.95-43.11
	99	22.87-59.08	27.63-53.35	31.16-49.33	34.38-45.82	36.02-44.08
41	95	(27.31-55.80)	31.27-51.28	34.12-48.15	36.66-45.45	37.93-44.12
	99	(23.72-60.04)	28.54-54.34	32.11-50.33	35.35-46.83	37.00-45.09
42	95	28.21-56.78	32.21-52.28	35.08-49.16	37.64-46.46	38.92-45.12
	99	24.57-60.99	29.45-55.33	33.06-51.33	36.32-47.83	37.98-46.10
43	95	(29.10-57.76)	33.15-53.27	36.05-50.16	38.62-47.46	39.91-46.13
	99	(25.42-61.95)	30.37-56.32	34.01-52.34	37.29-48.84	38.96-47.10
44	95	30.00-58.74	34.09-54.27	37.01-51.17	39.60-48.47	40.90-47.14
	99	26.27-62.90	31.28-57.31	34.95-53.34	38.27-49.85	39.95-48.11
45	95	(30.90-59.71)	35.03-55.27	37.97-52.17	40.58-49.48	41.89-48.14
	99	(27.12-63.86)	32.19-58.30	35.90-54.34	39.24-50.86	40.93-49.12
46	95	31.83-60.67	35.99-56.25	38.95-53.17	41.57-50.48	42.88-49.14
	99	28.00-64.78	33.13-59.26	36.87-55.33	40.22-51.85	41.92-50.12
47	95	(32.75-61.62)	36.95-57.23	39.93-54.16	42.56-51.48	43.87-50.14
	99	(28.89-65.69)	34.07-60.22	37.84-56.31	41.21-52.85	42.91-51.12
48	95	33.68-62.57	37.91-58.21	40.91-55.15	43.55-52.47	44.87-51.14
	99	29.78-66.61	35.01-61.19	38.80-57.30	42.19-53.85	43.90-52.12
49	95	(34.61-63.52)	38.87-59.19	41.89-56.14	44.54-53.47	45.86-52.14
	99	(30.67-67.53)	35.95-62.15	39.77-58.28	43.18-54.84	44.89-53.12
50	95	35.53-64.47	39.83-60.17	42.86-57.14	45.53-54.47	46.85-53.15
	99	31.55-68.45	36.89-63.11	40.74-59.26	44.16-55.84	45.89-54.11

Table 74. Critical values of the chi-square distribution. Reprinted with permission from Sokal and Rohlf 1981, Table 14.

To find the critical value of X^2 for a given number of degrees of freedom, look up ν df in the left column of the table and read off the desired values of X^2 in that row.

$\nu \backslash \alpha$	.995	.975	.9	.5	.1	.05	.025	.01	.005	.001	α / ν
1	0.000	0.000	0.016	0.455	2.706	3.841	5.024	6.635	7.879	10.828	1
2	0.010	0.051	0.211	1.386	4.605	5.991	7.378	9.210	10.597	13.816	2
3	0.072	0.216	0.584	2.366	6.251	7.815	9.348	11.345	12.838	16.266	3
4	0.207	0.484	1.064	3.357	7.779	9.488	11.143	13.277	14.860	18.467	4
5	0.412	0.831	1.610	4.351	9.236	11.070	12.832	15.086	16.750	20.515	5
6	0.676	1.237	2.204	5.348	10.645	12.592	14.449	16.812	18.548	22.458	6
7	0.989	1.690	2.833	6.346	12.017	14.067	16.013	18.475	20.278	24.322	7
8	1.344	2.180	3.490	7.344	13.362	15.507	17.535	20.090	21.955	26.124	8
9	1.735	2.700	4.168	8.343	14.684	16.919	19.023	21.666	23.589	27.877	9
10	2.156	3.247	4.865	9.342	15.987	18.307	20.483	23.209	25.188	29.588	10
11	2.603	3.816	5.578	10.341	17.275	19.675	21.920	24.725	26.757	31.264	11
12	3.074	4.404	6.304	11.340	18.549	21.026	23.337	26.217	28.300	32.910	12
13	3.565	5.009	7.042	12.340	19.812	22.362	24.736	27.688	29.819	34.528	13
14	4.075	5.629	7.790	13.339	21.064	23.685	26.119	29.141	31.319	36.123	14
15	4.601	6.262	8.547	14.339	22.307	24.996	27.488	30.578	32.801	37.697	15
16	5.142	6.908	9.312	15.338	23.542	26.296	28.845	32.000	34.267	39.252	16
17	5.697	7.564	10.085	16.338	24.769	27.587	30.191	33.409	35.718	40.790	17
18	6.265	8.231	10.865	17.338	25.989	28.869	31.526	34.805	37.156	42.312	18
19	6.844	8.907	11.651	18.338	27.204	30.144	32.852	36.191	38.582	43.820	19
20	7.434	9.591	12.443	19.337	28.412	31.410	34.170	37.566	39.997	45.315	20
21	8.034	10.283	13.240	20.337	29.615	32.670	35.479	38.932	41.401	46.797	21
22	8.643	10.982	14.042	21.337	30.813	33.924	36.781	40.289	42.796	48.268	22
23	9.260	11.688	14.848	22.337	32.007	35.172	38.076	41.638	44.181	49.728	23
24	9.886	12.401	15.659	23.337	33.196	36.415	39.364	42.980	45.558	51.179	24
25	10.520	13.120	16.473	24.337	34.382	37.652	40.646	44.314	46.928	52.620	25
26	11.160	13.844	17.292	25.336	35.563	38.885	41.923	45.642	48.290	54.052	26
27	11.808	14.573	18.114	26.336	36.741	40.113	43.194	46.963	49.645	55.476	27
28	12.461	15.308	18.939	27.336	37.916	41.337	44.461	48.278	50.993	56.892	28
29	13.121	16.047	19.768	28.336	39.088	42.557	45.722	49.588	52.336	58.301	29
30	13.787	16.791	20.599	29.336	40.256	43.773	46.979	50.892	53.672	59.703	30
31	14.458	17.539	21.434	30.336	41.422	44.985	48.232	52.191	55.003	61.098	31
32	15.134	18.291	22.271	31.336	42.585	46.194	49.480	53.486	56.329	62.487	32
33	15.815	19.047	23.110	32.336	43.745	47.400	50.725	54.776	57.649	63.870	33
34	16.501	19.806	23.952	33.336	44.903	48.602	51.966	56.061	58.964	65.247	34
35	17.192	20.569	24.797	34.336	46.059	49.802	53.203	57.342	60.275	66.619	35
36	17.887	21.336	25.643	35.336	47.212	50.998	54.437	58.619	61.582	67.985	36
37	18.586	22.106	26.492	36.335	48.363	52.192	55.668	59.892	62.884	69.346	37
38	19.289	22.878	27.343	37.335	49.513	53.384	56.896	61.162	64.182	70.703	38
39	19.996	23.654	28.196	38.335	50.660	54.572	58.120	62.428	65.476	72.055	39
40	20.707	24.433	29.051	39.335	51.805	55.758	59.342	63.691	66.766	73.402	40
41	21.421	25.215	29.907	40.335	52.949	56.942	60.561	64.950	68.053	74.745	41
42	22.138	25.999	30.765	41.335	54.090	58.124	61.777	66.206	69.336	76.084	42
43	22.859	26.785	31.625	42.335	55.230	59.304	62.990	67.459	70.616	77.419	43
44	23.584	27.575	32.487	43.335	56.369	60.481	64.202	68.710	71.893	78.750	44
45	24.311	28.366	33.350	44.335	57.505	61.656	65.410	69.957	73.166	80.077	45
46	25.042	29.160	34.215	45.335	58.641	62.830	66.617	71.201	74.437	81.400	46
47	25.775	29.956	35.081	46.335	59.774	64.001	67.821	72.443	75.704	82.720	47
48	26.511	30.755	35.949	47.335	60.907	65.171	69.023	73.683	76.969	84.037	48
49	27.249	31.555	36.818	48.335	62.038	66.339	70.222	74.919	78.231	85.351	49
50	27.991	32.357	37.689	49.335	63.167	67.505	71.420	76.154	79.490	86.661	50

Table 74. Continued.

$\nu \backslash \alpha$	.995	.975	.9	.5	.1	.05	.025	.01	.005	.001	α / ν
1	0.000	0.000	0.016	0.455	2.706	3.841	5.024	6.635	7.879	10.828	1
2	0.010	0.051	0.211	1.386	4.605	5.991	7.378	9.210	10.597	13.816	2
3	0.072	0.216	0.584	2.366	6.251	7.815	9.348	11.345	12.838	16.266	3
4	0.207	0.484	1.064	3.357	7.779	9.488	11.143	13.277	14.860	18.467	4
5	0.412	0.831	1.610	4.351	9.236	11.070	12.832	15.086	16.750	20.515	5
6	0.676	1.237	2.204	5.348	10.645	12.592	14.449	16.812	18.548	22.458	6
7	0.989	1.690	2.833	6.346	12.017	14.067	16.013	18.475	20.278	24.322	7
8	1.344	2.180	3.490	7.344	13.362	15.507	17.535	20.090	21.955	26.124	8
9	1.735	2.700	4.168	8.343	14.684	16.919	19.023	21.666	23.589	27.877	9
10	2.156	3.247	4.865	9.342	15.987	18.307	20.483	23.209	25.188	29.588	10
11	2.603	3.816	5.578	10.341	17.275	19.675	21.920	24.725	26.757	31.264	11
12	3.074	4.404	6.304	11.340	18.549	21.026	23.337	26.217	28.300	32.910	12
13	3.565	5.009	7.042	12.340	19.812	22.362	24.736	27.688	29.819	34.528	13
14	4.075	5.629	7.790	13.339	21.064	23.685	26.119	29.141	31.319	36.123	14
15	4.601	6.262	8.547	14.339	22.307	24.996	27.488	30.578	32.801	37.697	15
16	5.142	6.908	9.312	15.338	23.542	26.296	28.845	32.000	34.267	39.252	16
17	5.697	7.564	10.085	16.338	24.769	27.587	30.191	33.409	35.718	40.790	17
18	6.265	8.231	10.865	17.338	25.989	28.869	31.526	34.805	37.156	42.312	18
19	6.844	8.907	11.651	18.338	27.204	30.144	32.852	36.191	38.582	43.820	19
20	7.434	9.591	12.443	19.337	28.412	31.410	34.170	37.566	39.997	45.315	20
21	8.034	10.283	13.240	20.337	29.615	32.670	35.479	38.932	41.401	46.797	21
22	8.643	10.982	14.042	21.337	30.813	33.924	36.781	40.289	42.796	48.268	22
23	9.260	11.688	14.848	22.337	32.007	35.172	38.076	41.638	44.181	49.728	23
24	9.886	12.401	15.659	23.337	33.196	36.415	39.364	42.980	45.558	51.179	24
25	10.520	13.120	16.473	24.337	34.382	37.652	40.646	44.314	46.928	52.620	25
26	11.160	13.844	17.292	25.336	35.563	38.885	41.923	45.642	48.290	54.052	26
27	11.808	14.573	18.114	26.336	36.741	40.113	43.194	46.963	49.645	55.476	27
28	12.461	15.308	18.939	27.336	37.916	41.337	44.461	48.278	50.993	56.892	28
29	13.121	16.047	19.768	28.336	39.088	42.557	45.722	49.588	52.336	58.301	29
30	13.787	16.791	20.599	29.336	40.256	43.773	46.979	50.892	53.672	59.703	30
31	14.458	17.539	21.434	30.336	41.422	44.985	48.232	52.191	55.003	61.098	31
32	15.134	18.291	22.271	31.336	42.585	46.194	49.480	53.486	56.329	62.487	32
33	15.815	19.047	23.110	32.336	43.745	47.400	50.725	54.776	57.649	63.870	33
34	16.501	19.806	23.952	33.336	44.903	48.602	51.966	56.061	58.964	65.247	34
35	17.192	20.569	24.797	34.336	46.059	49.802	53.203	57.342	60.275	66.619	35
36	17.887	21.336	25.643	35.336	47.212	50.998	54.437	58.619	61.582	67.985	36
37	18.586	22.106	26.492	36.335	48.363	52.192	55.668	59.892	62.884	69.346	37
38	19.289	22.878	27.343	37.335	49.513	53.384	56.896	61.162	64.182	70.703	38
39	19.996	23.654	28.196	38.335	50.660	54.572	58.120	62.428	65.476	72.055	39
40	20.707	24.433	29.051	39.335	51.805	55.758	59.342	63.691	66.766	73.402	40
41	21.421	25.215	29.907	40.335	52.949	56.942	60.561	64.950	68.053	74.745	41
42	22.138	25.999	30.765	41.335	54.090	58.124	61.777	66.206	69.336	76.084	42
43	22.859	26.785	31.625	42.335	55.230	59.304	62.990	67.459	70.616	77.419	43
44	23.584	27.575	32.487	43.335	56.369	60.481	64.202	68.710	71.893	78.750	44
45	24.311	28.366	33.350	44.335	57.505	61.656	65.410	69.957	73.166	80.077	45
46	25.042	29.160	34.215	45.335	58.641	62.830	66.617	71.201	74.437	81.400	46
47	25.775	29.956	35.081	46.335	59.774	64.001	67.821	72.443	75.704	82.720	47
48	26.511	30.755	35.949	47.335	60.907	65.171	69.023	73.683	76.969	84.037	48
49	27.249	31.555	36.818	48.335	62.038	66.339	70.222	74.919	78.231	85.351	49
50	27.991	32.357	37.689	49.335	63.167	67.505	71.420	76.154	79.490	86.661	50